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By:

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About:

Towards a learning analytics dashboard focused on student motivation in a project-based learning context supported by ICT.

Submitted on: 02 / 07 / 2023 in Tiaret in front of the jury:

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Dedications

I present this culmination of my work as a tribute to my elder sister Omlkhir, whose presence and support have played a crucial role in my journey. The recognition and encouragement I have received from my family, especially my mother, have also been significant factors in my accomplishments. This achievement is a direct outcome of your unwavering love and support. May God bestow upon you a long and prosperous life.
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Yasmina

ABSTRACT

Abstract

In higher education, the mode of learning in groups or teams supported by ICT is taking an increasingly prominent role in students' learning journey. In this context, we are interested in examining the impact of this learning mode on students' motivation and engagement. Our objective is to propose a Learning Analytic Dashboard (LAD) that would reflect the motivation of the student and the team based on the traces of students' digital activities.

Keywords: Learning analytics, learning analytics dashboard, students' motivation.

Résumé

Dans l'enseignement supérieur, le mode d'apprentissage en groupe ou en équipe soutenu par les TICE prend de plus en plus de place dans le parcours d'apprentissage des étudiants. Dans ce contexte, nous nous intéressons à l'incidence de ce mode d'apprentissage sur la motivation et l'engagement des étudiants. Notre objectif est de proposer un Learning Analytic Dashboard (LAD) qui « reflèterait/représenterait/indiquerait » la motivation de l'étudiant et de l'équipe sur la base des traces des activités digitales des étudiants.

Mots-clés: Analyse de l'apprentissage, tableau de bord d'analyse de l'apprentissage, motivation des étudiants.

ملخص

في التعليم العالي، يأخذ نمط التعلم الجماعي أو التعاوني المدعوم بتقنيات تكنولوجيا المعلومات والاتصالات مكانًا متزايدًا في مسار تعلم الطلاب. في هذا السياق، نحن مهتمون بتأثير هذا النمط من التعلم على الدافعية والالتزام لدى الطلاب. هدفنا هو تقديم لوحة تحكم لتحليل التعلم التي ستعكس دافعية الطالب والفريق بناءً على آثار الأنشطة الرقمية للطلاب.

كلمات مفتاحية: تحليلات التعلم, لوحة تحليلات التعلم, دافعية الطلاب.

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General introduction

In the realm of modern education, Learning Management System (LMS) have become indispensable elements of the educational landscape. These platforms offer various advantages, including flexibility, accessibility, and interactive learning experiences (Agaçi, 2017). However, assessing and comprehending students' motivation levels within these digital learning environments can pose a challenge for the stakeholders (Talbi and Ouared, 2022). To address this, the concept of Learning Analytics (LA) has emerged as a powerful tool for analyzing student behavior and interactions to gain insights into their motivation levels (Lang et al., 2017).

A crucial aspect of this approach is the implementation of a Learning Analytics Dashboard (LAD), which provides the stakeholders with a comprehensive overview of students' and teams motivation. By utilizing data collected from diverse sources such as LMSs, including the students' interactions in a Project-based Learning (PjBL) environment, assessment results, discussion forum activity, and task completion time, the dashboard can generate meaningful visualizations and insights (Yigitbasioglu and Velcu, 2012).

The primary objective of a LAD focused on student motivation is to identify and present indicators in student behavior that reflect their motivation levels. These indicators can be identified through the analysis of several key factors. For example, monitoring the frequency and completion rate of activities, the level of engagement in collaborative tasks, and the quality of interactions with peers and instructors can offer valuable indicators of students and teams motivation.

Through the power of LA, stakeholders and administrators can gain a deeper understanding of student and their teams motivation, enabling them to intervene proactively and make informed decisions to enhance learning outcomes. With the aid of the dashboard, they can identify students who may be struggling, tailor instructional strategies, provide personalized support, and foster a motivating learning environment.

Incorporating a feedback component into the LAD allows teachers to send feedback to students, further enhancing the learning experience. This feature enables the stakeholders to provide targeted guidance and encouragement based on the insights gained from the analytics. By sharing constructive feedback, stakeholders can motivate students, address their specific needs, and promote continuous improvement (Corrin and De Barba, 2015; Sedrakyan et al., 2020).

The visualization capabilities of the LAD play a crucial role in presenting complex data in a user-friendly manner (Park and Jo, 2015). Through charts, graphs, and visual representations, the dashboard can illustrate student motivation levels over time and enable comparisons of individual motivation indicators. This visual empowers stakeholders to interpret the data effectively and make decisions to optimize the learning process.

This thesis is structured into four chapters. The initial chapter discusses the current state of the field. The first and second chapters are dedicated to theoretical aspects. The third chapter focuses on the design of the LAD, and finally, the fourth and final chapter explores the tools utilized during the implementation process and presents the ultimate outcome.

In conclusion, developing a LAD to detect and visualize students and teams motivation levels in an LMS represents an innovative approach to understanding and improving student engagement. By leveraging data-driven insights, stakeholders can identify behavioral indicators that reflect motivation levels and tailor their instructional strategies accordingly. The dashboard's visualizations provide educators with a clear and comprehensive view of student motivation, enabling them to make informed decisions, offer feedback, and foster a more motivating and effective learning experience for all students (Yigitbasioglu and Velcu, 2012).

CHAPTER 1

STATE OF THE ART

1.1 Introduction

In this chapter we want to give a thorough overview of our project's background. We start by discussing the adoption of Information and Communication Technologies (ICT) in the educational sector and how it affects the teaching and learning processes, motivation, LA, LAD, engagement and then, the approach of PjBL is discussed, along with its effectiveness in inspiring students and the significance for measuring motivation in such settings.
Additionally, we will discuss previous researches and writings that are pertinent to our case study and highlight their contributions to the area of education. We hope to establish the importance of our study and its possible implications for the field by placing it within this wider framework.

1.2 Background

The approaches used in teaching and learning have undergone substantial modifications as a result of the usage of ICT in education. Educators are utilizing ICT tools and systems to improve learning outcomes, encourage student involvement, and enrich the educational experience as a result of the rapid improvements in technology. An introduction of LMS, LA, LADs, motivation in education, and PjBL is given in this background section.

1.2.1 Information and communication technologies integration into the educational sector

Statista[1] estimates that there will be 6.92 billion smartphone users worldwide in 2023, which translates to 86.29% of the world's population having a smartphone. This huge number tells a clear short story about the ICT existence in our lives.

Currently, ICT are having an impact on all facets of human life. They are taking on significant parts in the workplace, commerce, entertainment, health care ..etc. And certainly education is not an exception (Sharma, 2021).

In general ICT, is a tool that lets us communicate with one another and conduct informational searches (Bosamia, 2013), but in education it is somehow related to the history of the e-learning term. This term was founded in 1997 by Elliott Masie[2], who define it to be the use of network technology to develop, deliver, select, administer, and extend learning. In 1998, Jay Cross[3] said: *"eLearning is learning on Internet time, the convergence of learning and networks. ELearning is a vision of what corporate training can become, eLearning is to traditional training as eBusiness is to business as usual."* (Cross, 2004).

The use of numerous technologies, including computers, tablets, smartphones, the internet, educational software, online libraries, information systems, and multimedia materials, is referred to as ICT integration into education (Bosamia, 2013). As mentioned by Hernandez (2017), *"How to address this technological approach to the teaching and learning process?"* is currently the key concern. And saying that ICT integration is successfully done, still somehow related to the teacher's ability of organizing the learning environment.

From another point of view, Mir (2019) said that ICT integration is facing some challenges as:

a) Lack of awareness or misunderstanding about technology and its use are two primary barriers to ICT integration in education.

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[1] Statista is an online resource that provides statistics, studies, market insights, consumer insights, and corporate insights in German, English, Spanish, and French (Enrevselujr, 2023).

[2] Elliott Masie is a thought-provoking, captivating, and interesting researcher, educator, analyst, and speaker who is interested in how technology, education, and the workplace are changing. Elliott is credited with being the first analyst to adopt the term "eLearning" and has argued in favor of a responsible deployment of learning and collaboration technologies to increase the efficiency and profitability of businesses.(MASIE, 2022)

[3] James Calvin Cross Jr, an American futurist, the one who popularized the term "e-learning" and promoted informal learning in professional contexts Vysotsky (2023).

c) Policies that discriminate against rural and urban areas and are insufficient.
f) The inadequacy of ICT services in higher education institutions to maintain themselves.
g) Lack of or poor networking infrastructure in rural and far-off locations.
h) Faculty and students with low ICT literacy.
i) The absence of suitable ICT infrastructure resources in the educational sector.

But even with these challenges, the integration of ICT in the educational sector is getting wider day by day.

Web based learning and learning management systems

Because it involves online course content, web-based learning is frequently referred to as online learning or e-learning. The internet makes it feasible to participate in discussion forums via email, video conferences, and live lectures (video streaming). Static pages, such as printed course materials, may also be provided as part of web-based courses (Wasim et al., 2014). As stated by Turnbull et al. (2020), LMSs are frequently used in educational institutions (e.g. Moodle, TalentLMS, Schoology), and they are considered to be web-based software platforms that offer an interactive learning environment for online courses. Stone and Zheng (2014) mentioned that an LMS is an integrated web-based platform that serves as a centralized information system for managing learning content and organizing learning activities. It encompasses various components and functionalities that support both formal and informal learning processes. These include learning management, content management, course management, and other related features. Essentially, an LMS provides a comprehensive technological framework to facilitate various aspects of the learning experience. When students use their individual accounts to access these systems we can see that as a result, the usage of ICT in the teaching-learning process will significantly help to meet the needs of every student for learning wherever and whenever he chooses (Bhasin, 2012).
Another term is related with the integration of ICT in education, massive open online courses, it stands as an excellent online resource that help speed up the process of studying in any kind of subject (Palacios Hidalgo et al., 2020).

Universities adoption of the information and communication technologies

Research on the adoption of ICT has drawn a lot of attention from throughout the world, with interest spanning various systems and applications in various contexts/settings. Studies in this area are vital since education greatly promotes socio-economic growth, and ICT is a key tool, universities use ICT to access and share information in real time, as well as to update curricula, instructional methods, and research in order to meet ideal academic objectives (Eze et al., 2013). Over the past two decades, the Kingdom of Saudi Arabia government and other stakeholders in the education sector, including university administration and scholars, have invested millions of dollars to implement ICT in the educational system (Basri et al., 2018). As cited by Murshitha and Wickramarachchi (2013), the installation of an LMS is increasingly required at universities in the knowledge era since it improves the environment for teaching and learning. Although approval and use by lecturers[4] can help LMS adoption in universities, it endures over time thanks to students' ongoing acceptance and use.

Students adoption of the information and communication technologies

The students adoption of ICT in their education process was so smooth, according to a survey conducted by Samarawickrema and Stacey (2007), in the Australian university, many students have embraced web-based learning and LMSs. Particularly in cases where students move around, LMS features like communication opportunities such as group problem-solving, peer observation, and peer evaluation were frequently cited as reasons for adoption. One of the highlighted reasons of ICT adoption by students is their environment, the impact of technology and smartphones on students is evident, and especially during the Corona pandemic, when direct face-to-face communication where forbidden due to health concerns (Firmansyah et al., 2021).

Students recognize the essential role of ICT in their academic curriculum and express a strong desire to access ICT tools. Notably, students with higher grades and those studying social science disciplines display a heightened inclination towards embracing ICT. It is crucial to acknowledge the importance of facilitating students' access to ICT to enhance their academic performance while promoting a healthy balance between

[4] Although the definition of the term varies slightly from country to country, lecturer is an academic rank found in many universities. It typically refers to a subject-matter expert who has been recruited on a full- or part-time basis to educate. They might even carry out study (Chris, 2023).

productive usage and excessive engagement with social media (Basri et al., 2018).

1.2.2 Learning analytics, educational data mining and academic analytics

Now, that knowledge is distributed everywhere thanks to ICT and web-based learning, the volume of education data collected from LMSs get to be bigger day by day. A well-known issue associated with the ongoing growth in data that must be handled is information overload. LA is one of the "big data" methods that scholars in education are interested in applying (Lang et al., 2017).
One of the most famous definitions of LA is *“the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs”*, by Siemens and Baker (2012). LA have gotten a lot of interest since they were first discussed in the new media consortium report[5] 2012. The following year, the new media consortium horizon report 2013 listed LA as one of the significant changes in education and learning that had been made possible by technology (Wibawa et al., 2021). LA from a traditional perspective is the evaluation, gathering, analysis, and reporting of information on students and their environments (Figure 1.1 represents an overview of the LA process), in order to understand and improve learning and the settings of environments in which it takes place (Scheffel et al., 2014; Mian et al., 2022).

On the recent past, determining with accuracy and sufficient foresight in the learning process whether a student in a course or in a study program is unlikely to complete it successfully was a common LA question. Since then, the field of LA has expanded as it has become possible to monitor student and teacher behavior through LMSs (Lang et al., 2017).
On another hand Educational Data Mining (EDM) is a relatively new scientific discipline that has emerged in recent years as a distinct field. While researchers have been collecting and analyzing data from educational software for a long time, it is only recently that EDM has been recognized as a specialized area of study (Scheuer and McLaren, 2012). EDM is used to address educational issues. It is an interdisciplinary

[5] A network of more than 200 museums and educational institutions committed to advancing technology and education. The horizon report, a document that predicted the use of technology in education over the following five years, was released by the new media consortium and EDUCAUSE (Cynthia, 2019)

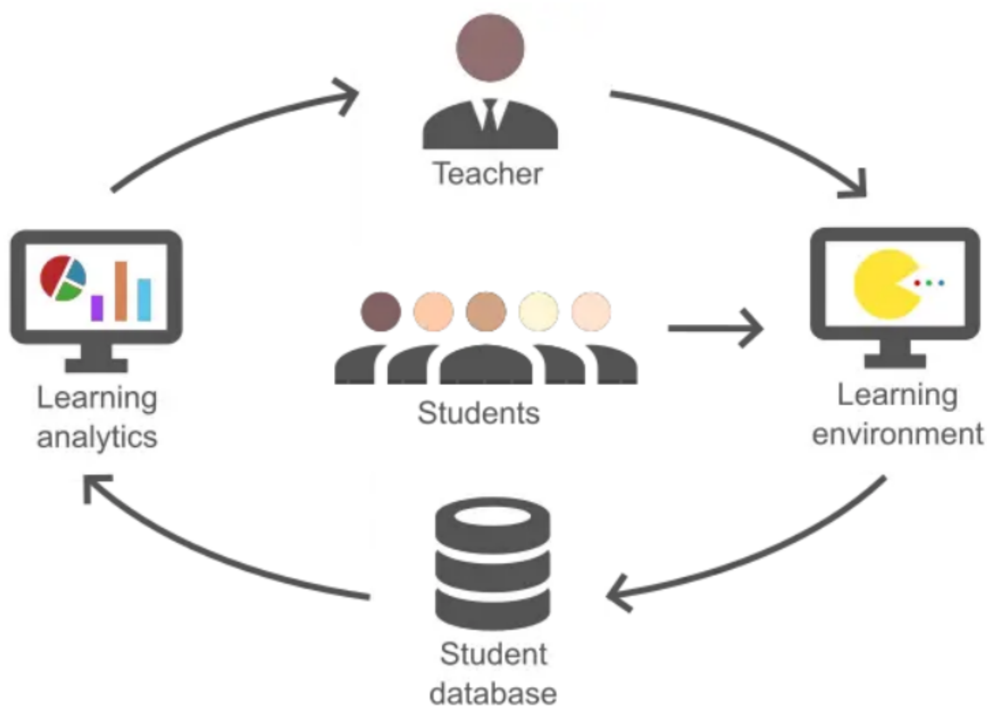

Figure 1.1: An overview of the learning analytics process.
(Neural, 2021)

field of study, applies machine learning, statistics, data mining, psycho-pedagogy[6], and many other techniques to various educational data sets (Dutt et al., 2017). Figure 1.2 represents an overview of how EDM methods are applied.

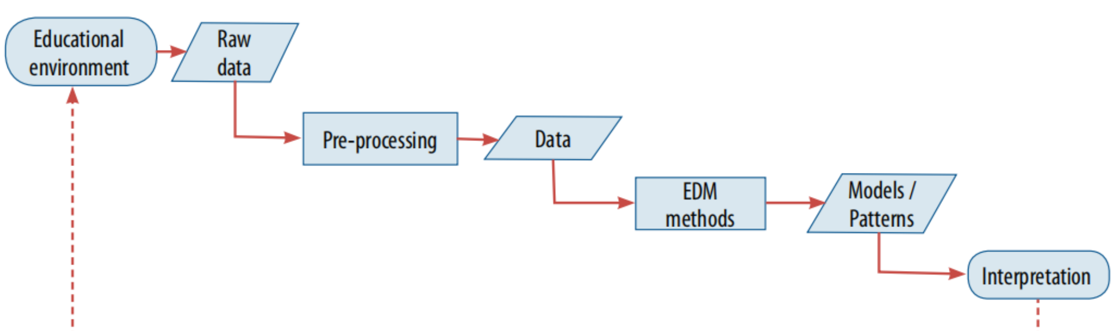

Figure 1.2: An overview of how educational data mining methods are applied.
(Liñán and Pérez, 2015)

[6]It is the area of psychology that is in charge of people's education, regardless of their age or area of endeavor. The right didactic and pedagogical techniques are employed, and at the same time, the person's emotional and psychological state is addressed concurrently (Roldan, 2023).

Field	Stakeholders	Objectives	Methods	Data
Academic Analytic	Educational institutions	Enrolment managing, Prediction, Marketing, Decision making	Statistical techniques	Education environments data
Educational Data Mining	Teachers, Students	Improving the learning process by converting data into relevant information	Data mining techniques (Clustering, Association, Classification)	Education environments data
Learning Analytics	Learners, Teachers, Institutions	Recommendation, prediction, admissions, marketing, adaption, personalization	Quantitative methods and classification clustering, association	Education environments data

Table 1.1: Differences between academic analytics, learning analytics and educational data mining (Paz and Cazella, 2019).

Both EDM and LA use the majority of techniques that are suitable to educational data. Prediction, classification, and relationship mining are the most popular (Liñán and Pérez, 2015). Computer-based learning systems now enable detailed logging of user-system interactions, including key clicks, eye-tracking, and video data, opening up opportunities to study how students learn with technology. EDM focuses on developing and applying computerized methods to detect patterns in large educational data collections that would otherwise be challenging to analyze due to their volume. EDM considers various data sources such as individual and collaborative student interactions, administrative data, demographic data, and student affect. It utilizes methods from data mining, emphasizing educational data and addressing both theoretical and practical learning problems. EDM projects involve data acquisition, preprocessing, mining, and result validation (Scheuer and McLaren, 2012).

About academic analytics, the higher education institutions receives the data it needs to support operational and financial decisions through the academic analytic process, which also serves as a roadmap for strategic actions (Paz and Cazella, 2019). The table 1.1 represents a brief comparison among the three fields: academic analytics, EDM and LA.

1.2.3 Learning analytics dashboards

It is clear that analyzing vast volumes of data is done to identify insights, and visualizing the outcomes for quick comprehension looks to be a hard part without the use of a LAD that is a tool to display the online behavior patterns of students (Yigitbasioglu and Velcu, 2012).

Dashboards are defined as visual displays of the most important information needed to achieve one or more objectives, consolidated and arranged on a single screen so the information can be monitored at a glance (Abduldaem and Gravell, 2019), hand to hand with LA they become to be a powerful tool that gives to higher education experts the chance for taking effective decisions (Yigitbasioglu and Velcu, 2012).

According to Park and Jo (2015), the term *"dashboard"* originally appertained to a board or panel on a horse-drawn carriage or machine that shielded the innards from slush or dirt splashes. Over time, it converted into a control panel in motorcars, furnishing driving- related information. In the business world, dashboards surfaced as systems for managing performance, covering productivity, assaying cost-effectiveness, and enhancing customer satisfaction. These dashboards offered a quick overview of pivotal performance pointers (key performance indicators) and touched off cautions when diversions from predefined targets passed.

The appearance of big data and its wide operation have led to the development of enterprise dashboards, akin to aircraft dashboards that incorporate numerous pointers. These dashboards have evolved to be SMART(synergetic, monitor key performance indicators, accurate, responsive, and timely) and IMPACT(interactive, farther data history, substantiated, logical, collaborative, and traceability). Also, the rise of information technology and digital bias has amplified the significance of dashboards in various professional and everyday surrounds. Dashboards are defined as *"visual displays of the most vital information demanded to achieve one or farther objects, consolidated on a single computer screen for easy monitoring"*.

Applying these dashboard generalities to LAD yields an interactive, nonfictional, substantiated, and logical monitoring interface that reflects scholars' knowledge patterns, status, performance, and relations. Dashboards incorporate visual rudiments like charts, graphs, pointers, and alert mechanisms. While external visualization holds significance, the core of the system lies in data- mining processes that prize unknown and implicit information from patterns of connections within extensive and complex datasets.

1.2.4 Motivation theories and engagement

Motivation is one of the key conditions to students success. And it is known that the students with a high motivation level are more to be engaged in their studies (Nayir, 2017; Fleur et al., 2020). Students' motivation is regarded as an encouraging force in the teaching and learning process that affects all educational levels, both in relation to the amount of time students spend studying as well as their academic performance and achievements, and it significantly influences their ability to achieve immediate happiness in their lives (Leal et al., 2013). Motivation to learn is defined as not just an energy that makes students learn but also directs their activities toward their learning goals (Wardani et al., 2020).

Motivation theories

According to Gopalan et al. (2017), the theoretical idea of motivation is used to explain human behavior. Humans can react and meet their wants when they are motivated to do so. The construct that causes someone to want to reproduce a behavior and vice versa can also be considered a form of motivation. The mechanism that initiates, directs, and sustains goal-oriented behaviors is referred to as motivation. Basically, it motivates people to behave in order to fulfill a need, expect, or goal.

Self determination theory

Different motivational factors, including ego-involvement[7], personal value, and intrinsic interest, have an impact on student achievements. According to self-determination theory, these motivational styles co-occur to varying degrees and tend to have various effects (Howard et al., 2021). The self-determination theory has received a great deal of attention in the area of motivation in education. Some researchers claim that this theory can be stated up as a continuum of self-determination that identifies three different

[7] Ego-involvement is the level to which we perceive an attitude object as important or significant, also known as attitudinal involvement, personal involvement, or self-reliance, can vary. It is essential to consider the centrality of attitude and the significance it holds in shaping our evaluations (N., 2013).

types of motivation that differ qualitatively based on the internalization of external rules of behavior (Leal et al., 2013). First, intrinsic motivation is the psychological urge to engage in a behavior for the enjoyment, satisfaction, or fun that comes from engaging in the behavior. Second, extrinsic motivation refers to the psychological condition that arises when people are motivated to accomplish goals that are distinct from the pleasures associated with the conduct itself. Third, amotivation is a condition when neither intrinsic nor external causes motivate behavior. Students who are amotivated either do not understand how their actions relate to the desired outcome or believe they are not capable of completing the task at hand (Howard et al., 2021).

Self efficacy theory

The self-efficacy theory has been widely used since it was first introduced to psychological literature, particularly in situations related to therapy, health, business, and education. Collectively, the empirical evidence has proven the theoretical claim that self-efficacy is an important motivating factor (Schunk and DiBenedetto, 2021). The belief that one can effectively carry out the behaviors required to attain a desired goal is how self-efficacy is initially defined, as mentioned by Lishinski et al. (2016). Self-efficacy beliefs influence how much effort people are willing to put forth as well as how well they handle and persevere in the face of difficulties. Self-beliefs serve a self-regulating role by acting as a bridge between an individual's values or goals and the actions they use to attain them. The self-efficacy theory strength is that it frequently explains modest correlations between past ability and accomplishment using these kinds of self-beliefs (Lishinski et al., 2016).

On the other hand as mentioned by Schunk (1995), self-efficacy has an impact on activity selection, effort, determination, and success. People who have strong self-efficacy for completing a task participate more willingly, work harder, persist longer when they run into challenges, and achieve at higher rates than those who have low self-efficacy.

Engagement

Compared with motivation, engagement is no less important, Because engagement is a crucial mechanism for acquiring knowledge both inside and outside of educational contexts (Saeed and Zyngier, 2012). As mentioned by Lee et al. (2019), the degree of effort or interaction between the amount of time or learning resources that create learning outcomes and experiences is known as student engagement. A student who is engaged in their learning shows dedication to the subject matter and approaches the learning process with enthusiasm and care because they place value on it. This level of engagement enables the student to persevere through challenges and setbacks they may face during assignments, as they are able to find personal value and meaning in their work (Nayir, 2017).

Relation between motivation and engagement

The connection between motivation and engagement is still up for discussion. According to some authors, engagement is an externalization of motivation and a result of motivation. Engagement combines self-determined extrinsic motivation with action that is driven by internal motivation (De Loof et al., 2021). For Saeed and Zyngier (2012) engagement is seen in the literature as being crucial for improved learning results for all students, along with motivation. It is believed that motivation is both a requirement and a component of student participation in learning. In addition to being a goal in and of itself, student engagement in learning also serves as a vehicle for students to achieve successful academic outcomes. This is significant because genuine engagement may result in improved academic performance over the course of a student's academic career.

1.2.5 Project-based learning and motivation

During the learning process, educators employ various teaching approaches, such as PjBL, to facilitate the learning experience.

PjBL is an inquiry-based educational approach that involves learners in the development of knowledge by having them complete significant tasks and create practical solutions (Guo et al., 2020), PjBL can be described using three concepts, which state that learning occurs within particular contexts, requires active engagement from the learner, and results in achieving goals through social interactions and the exchange of knowledge and ideas (Kokotsaki et al., 2016). Students that participate in PjBL have the ability to independently identify both simple and complicated problems, develop solutions, and conduct joint research to find solutions. In a collaborative educational environment, learning takes place as students work together to solve issues and present their findings. Teachers and students must assume roles that are different from those to which they are used in this type of environment (Shin, 2018).

As mentioned in many studies (Ocak and Uluyol, 2010; Guo et al., 2020; Kokotsaki et al., 2016; Shin, 2018), and others, students participation in PjBL increases the motivation level. Ocak and Uluyol (2010) studied the effect of PjBL on students intrinsic motivation considering it as the most important type of motivation, according to many researches they mentioned that extrinsic motivation is significantly less significant and effective than intrinsic motivation. Their investigation revealed that group project participants ran across a variety of issues. This was due to the fact that students were unable to collaborate fully, and issues with student distribution of courses were believed to be what negatively impacted intrinsic motivation. They also stated that the PjBL environment put pressure on students' efforts to complete assignments and resulted in more regular information interchange. In another study Baş (2011) found out that students learned responsibility through group work while participating in PjBL, which also gave them the will to study. This allowed them to gain knowledge by hearing various viewpoints and comprehending others' points of view during the session.

1.3 Problem setting

In a PjBL environment, students collaborate in small groups or teams to address complicated issues, develop solutions, and apply what they have learned to situations that they might face in the real world (Guo et al., 2020). The level of student motivation, which can have a substantial impact on their learning results and involvement in the project, can be difficult for educators and higher education experts to assess and measure in such a setting (Talbi and Ouared, 2022).

Students' motivation, which drives their interest, effort, and persistence in the project and might affect their capacity to attain the required learning objectives, is a crucial component of their education (Ramaha and Ismail, 2012). We suggest creating a LAD to visualize the students' motivation levels, which are tracked and recognized based on

their interactions in the LMS, in order to address this problem. The PjBL environment, where students engage with the course materials, their classmates, will be hosted by the LMS.
In order to determine indicators of students' motivation levels, such as their participation in activities, communication and collaboration with peers, the proposed LAD will analyze students' patterns of LMS interactions. The higher education expert can help modify the project activities and learning materials to better boost student motivation and engagement thanks to the feedback option offered by the LAD. By monitoring and identifying students' levels of motivation in a PjBL setting, this LAD will assist educators and higher education experts in better understanding the elements that affect student motivation and will enable them to offer customised support to students who may be having difficulties. This in turn could improve the learning results, engagement, and general satisfaction of students.

1.4 Related works

Numerous research have focused on evaluating motivation in PjBL contexts in an LMS. Depending on how students behave in LMS courses, a classification model was built by Babić (2017), to predict students' academic motivation. Lam et al. (2010) studied the relationship between instructors' motivation and desire to stick with PjBL and school support. For students at vocational high schools, a project-based curriculum was created, and its impact on students' learning motivation and problem-solving skills was studied by Chiang and Lee (2016). Hira and Anderson (2021) found that a number of elements regarded as essential to online learning motivation are embodied in PjBL. Lam et al. (2009) compared the intrinsic motivation of teachers and students in PjBL. Self-determination theory was used by Oh et al. (2020), to develop a paradigm for employing PjBL to increase student motivation. Nuramalina et al. (2022) compared the scores of learning motivation before and after PjBL was implemented in the experimental class to assess data on learning motivation. Nuramalina et al. (2022) evaluated how motivation, PjBL, and visual, auditory, and kinesthetic learning styles affected high school students' critical thinking abilities.

The use of LADs has become widespread in higher education to offer insights on student performance and engagement. However, there has been limited exploration of the impact on motivation. A few studies have focused on the development and design of these dashboards (Aguilar, 2023). For example, Xin and Singh (2021) conducted a review of pertinent research and existing LADs, pinpointed dashboard requirements, and suggested a data visualization approach for a LAD. Additionally, Jivet et al. (2018) examined how learning sciences and analytics intersect by analyzing which educational concepts inform the creation of LADs for learners.

The utilization of student-facing dashboards and their influence on motivation has been studied by Toohey et al. (2019). Verbert et al. (2013) have created LADs that display learning traces for both learners and teachers. Jivet et al. (2018) have examined the theoretical basis that should inform the design of learning dashboards. Smith (2020) has discussed how the use of student-facing LADs has expanded, empowering students and increasing motivation beyond reporting systems used by teaching or administrative staff. Ibarra et al. (2016) have suggested a conceptual framework for analyzing LA applications for learners and teachers. Decan et al. (2019) have explored various dashboards for open source software development analytics. Finally, Santos et al. (2013) have developed a learning dashboard with a specific focus on motivation. Overall, these works have addressed different facets of LADs, including design, development, deployment, motivational implications, data visualization strategies, theoretical foundations, and diverse applications.

1.5 Conclusion

In this chapter, we provided an overview of the background of our work. We discussed the adoption of ICT in the educational sector and its impact on teaching and learning processes. PjBL was explored, highlighting its effectiveness in inspiring students and the importance of measuring motivation in such settings.

We also discussed previous research and its contributions to the field of education. The integration of ICT into education was addressed, along with the challenges it faces, such as lack of awareness, inadequate infrastructure, and low ICT literacy among faculty and students.

Web-based learning, LMSs, and massive open online courses were introduced as key elements of ICT integration in education. The adoption of ICT by universities and students was examined, emphasizing the role of ICT in accessing information, updating curricula, and enhancing the teaching and learning environment. Furthermore, we explored the concepts of LA, academic analytics, and EDM. These fields involve analyzing educational data collected from LMSs, aiming to understand and improve learning outcomes. LADs were highlighted as powerful tools for visualizing student behavior patterns and supporting decision-making in higher education. Motivation and engagement were discussed as important factors in student success. Motivation was defined as the driving force behind behavior, while engagement referred to the level of effort and interaction in learning. The relationship between motivation and engagement was explored, highlighting engagement as an externalization of motivation and a crucial aspect of improved learning outcomes.

Lastly, PjBL was introduced as a valuable approach to student participation and engagement. Numerous studies have emphasized the benefits of PjBL in fostering critical thinking, collaboration, and problem-solving skills among students. By placing our study within this wider framework, we established its importance and potential implications for the field of education.

In the upcoming chapter, we will examine the connection between motivation and LA, explore the integration of LADs, and delve into the necessary techniques required to establish this relationship.

CHAPTER 2

UNVEILING STUDENT MOTIVATION: LEVERAGING LEARNING ANALYTICS FOR INSIGHTFUL ANALYSIS AND VISUALIZATION

2.1 Introduction

This chapter explores the fascinating connection between LA and motivation in education. It focuses on the development of a motivation dashboard that utilizes data analytics to gain insights into student motivation levels. The chapter discussed the relationship between LA and motivation. It highlights how the motivation dashboard can leverage various data sources to provide valuable insights into student motivation, enabling stakeholders to understand the factors that influence it. By examining the intersection of LA and motivation, this chapter aims to demonstrate how LA can enhance our understanding of student motivation and improve learning outcomes.

2.2 Learning analytics and motivation

The interesting link between LA and motivation detection is explored in this section. We investigate the theoretical foundations, approaches, and applications that advance our comprehension of how LA can successfully pinpoint and quantify students' motivation. In order to shed light on the potential to enhance educational practices and results.

2.2.1 The relation between learning analytics and motivation

The connection between LA and motivation is strong and mutually beneficial (Aguilar et al., 2021). LA involves collecting and analyzing data from educational settings to understand students' learning behaviors and outcomes (Avella et al., 2016). Motivation, on the other hand, plays a vital role in learning as it drives students' engagement, effort, and persistence (Ryan et al., 2021). By utilizing LA, valuable insights can be gained into student motivation through the analysis of various data sources (Valle et al., 2021).

LA can track how students interact with learning materials such as course content, discussion forums, and assessments, allowing for the identification of engagement patterns (Kaliisa and Dolonen, 2022). Analyzing data on the frequency and duration of these interactions provides insights into their motivation levels. For instance, students who consistently spend more time engaging with course materials may indicate higher motivation (Esra and Sevilen, 2021).

LA can also identify students at risk of disengagement or low motivation by monitoring data on participation, assessment scores, or interactions (Queiroga et al., 2020).

2.2.2 Learning analytics and motivation measurement

LA is frequently used to identify patterns (Jo et al., 2014), These patterns can provide valuable information and insights about learners' motivation levels and even more, LA can help in motivational interventions to support studens' engagement and identify students who may have trouble educationally (Herodotou et al., 2020).

Morever, the field of LA gives new opportunities in motivation measurement. According to Lang et al. (2017), some LA researches covered the in between motivation measurements and successful completion of a massive open online course. Some others used LIWC[1] word categories to measure the students' level of motivation and cognitive engagement. Several measurement models utilized in the examination of motivation, emotion, and cognition. On another hand Tempelaar et al. (2020), based on the 'Motivation and Engagement Wheel' framework, their findings highlighted the connection between behavioral trace data and the factors that influence measured engagement.
Wong et al. (2019) discussed about two studies that looked at different theories of motivation. In both of these studies, surveys were utilized to quantify motivation rather than identifying behaviors of learners in log data as indicators for motivation. The two studies serve as excellent illustrations of the significant connection between learning theories and LA. As a result, it appears that LA can aid in quantifying learning behav-

[1]LIWC(Linguistic Inquiry and Word Count) a text analysis program that determines the proportion of words in a given text that fall into one or more of over 80 linguistic, psychological, and topical categories that represent diverse social, cognitive, and effective processes (Tausczik, 2014).

iors to improve the comprehension of motivation.

As mentioned by Ilyas and Liu (2020), the existence of various motivation indicators give a chance and can be used to measure student motivation.

Some studies investigated the measurement of motivation before and after a case of study, mentioning that some of them had different goals of ours, for example, Fleur et al. (2020) measured the students motivation levels in two categories with and without the access to a LAD. Babić (2017) used machine learning methods as Artificial neural networks, classification tree and Support vector machines to predict students academic motivation. Amraouy et al. (2020) detected the motivation state of learners in an online learning environments.

Babić (2017) used only raw log data collected from the LMS courses. Amraouy et al. (2020) focused on the term *Digital footprints*, which are the traces students leave when interacting with a course material in an LMS. A digital footprint or trace was defined in their study as a semester's worth of observational learning behaviors, such as the quantity of emails, discussions, and assignments read, along with the quantity of web pages, content pages, and files viewed, as well as application learning behaviors, such as the quantity of emails sent, discussions posted, assessments completed, and assignments submitted.

Talbi and Ouared (2022) detected the students motivation in a high level of abstraction based on the student Learning Behavior Indicators and Content Progress Indicators. We mentioned in the first chapter the relation between motivation and engagement, due to this relation the engagement indicators can also be a part of Motivation Indicators.

2.2.3 Learning analytics levels

According to Hantoobi et al. (2021), there are four primary levels in LA: descriptive, diagnostic, predictive, and perspective. Figure 2.1 represents these levels and the purposes of each one.

In our case we are more interested in the first level. The descriptive level enables us to detect and comprehend what's happening in the learning environment.

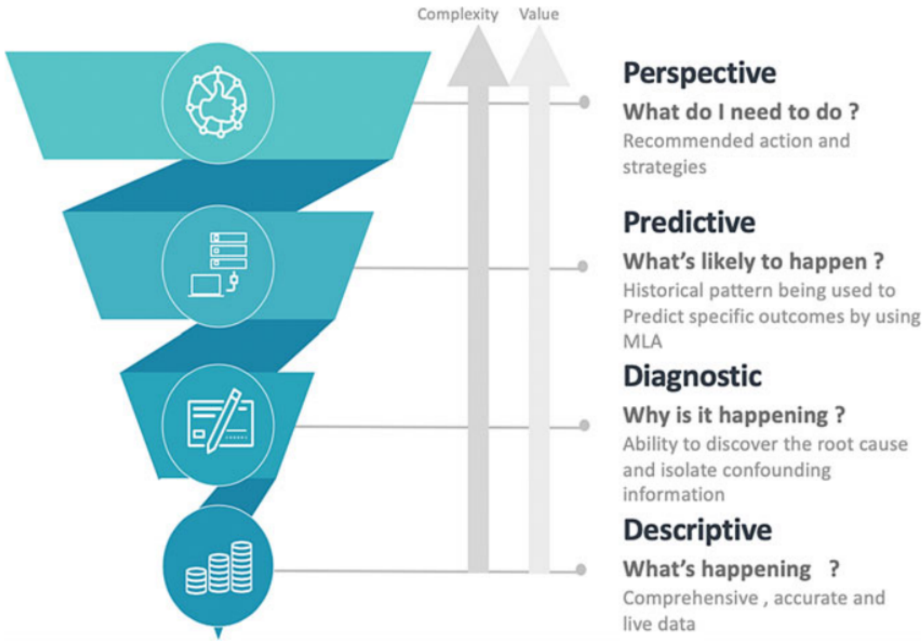

Figure 2.1: The main learning analytics levels.
(Hantoobi et al., 2021)

Descriptive learning analytics

Using educational data, the descriptive LA helps to understand the past and present. Instead of making predictions about the future, descriptive LA puts previous data into perspective using visuals and other understandable techniques. These techniques include comparative techniques like displaying the mean and median values of the dataset's feature values. Understanding the history and current data is essential in many learning contexts, even if predictive and prescriptive LA typically require more extensive data modeling than descriptive LA (Costas-Jauregui et al., 2021).

Indicators

The descriptive LA rely on indicators (Ahmad et al., 2022). In the Oxford glossary, indicators are defined to be *"a sign that shows you what something is like or how a situation is changing."*. This definition is close to our vision because according to Ahmad et al. (2022), an indicator is the end result of analyzing one or more metrics and provides a more thorough picture of a certain learner state such as engagement and performance. Additionally, as stated by Djouad and Mille (2018), an indicator is a mathematical variable. The variable may have symbolic, logical, or alphanumeric values and may be qualitative or quantitative.

There exists many types of indicators, we mention:

1. Learning Behavior Indicators (LBIs): According to Talbi and Ouared (2022); Maraza-Quispe et al. (2020), LBIs include engagement in discussions, timing of starting activities, timing of completing activities, number of views to the course presentation, number of accesses to the course..ect.

2. Content Progress Indicators: content progress indicators cover the completed course activities, submitted discussion prompts, current course grade..ect (Talbi and Ouared, 2022).

3. Key Performance Indicators: Academic program assessment and student success rate are considered to be key performance indicators (Badawy et al., 2018).

Metrics

In descriptive LA, metrics are used to create indicators (Ahmad et al., 2022; Djouad and Mille, 2018).

"A system or standard of measurement ,(business) a set of numbers or statistics used for measuring something, especially results that show how well a business, school, computer program, etc. is doing.". This is the definition of a metric according to the Oxford glossary, while according to Ahmad et al. (2022), the data collected from the interactions between learners and LMSs must be categorized into a relevant unit of measurement such as views, login/logout frequency and time, postings, etc. In order to make sense of them. In their study this measurement system is referred to as a metric.

Motivation indicators

Motivation indicators are still up to discussion, but in this section we will explore the main motivation indicators.

First of all, Amraouy et al. (2020), provided four motivation indicators based on the Vallerand scale (Academic Motivation Scale). The four motivation indicators were: collaboration indicator, effort indicator, free choice indicator and participation quality indicator.

According to self-determination theory, the Vallerand scale is one of the scales that is most frequently used to assess the regulation of motivation. This measure was examined for factorial invariance across gender and time, and it was validated by a variety of demographics, including English and French-speaking students, from high school to university levels (Amraouy et al., 2020).

In another study, according to Cocea (2006), performance is defined as the result of motivation and serves as an indirect indicator of motivation, at this point, it is clear that motivation indicators may also include key performance indicators.

The interest can also be an indicator that helps in student motivation measurement, the number of clicks in an LMS can be a good metric to calculate the interest indicator (Iqmaulia and Usman, 2019).

2.3 Learning analytics dashboards, motivation and feedback

LA gave a lot of interest in dashboards as tools that might offer users pertinent insight, provoke user reflection, and even inform interventions aimed at enhancing learning and improving the standards of the student experience (Matcha et al., 2019).

2.3.1 Learning analytics dashboards and motivation

The majority of existing LADs solely rely on indicators of learner performance. These indicators include information such as identifying areas where a learner is excelling or struggling, the amount of content completed, the time spent, and a comparison of learners' progress to teacher-specified or peer scores (Sedrakyan et al., 2020).
Several studies investigated the impact of LADs on students motivation (Jivet et al., 2020; Fleur et al., 2020; Park and Jo, 2015). Jivet et al. (2020) stated that motivation may help students find out what is relevant in a LAD. Throughout their research, it became evident that a tool as a LAD is capable of assisting students in comprehending their learning behavior like performance, engagement and motivation upon commencing their studies at a higher education institution could be extremely valuable.
After being convinced that motivation is related to academic achievement, Fleur et al. (2020), developed a LAD to enhance students motivation, they found out that the stu-

dents who had access to the dashboard ended up to be more motivated.
These studies and researches provide us a sense of how a dashboard, which uses LA to analyze numerous data sources, might give useful insights into students' motivation.

2.3.2 Learning analytics dashboards and feedback

The advancement of technology has sparked considerable curiosity in investigating learner behavior data using LA. This aims to offer both learners and instructors feedback that focuses on the learning process, presented as dashboards (Sedrakyan et al., 2020), the provision of feedback to students through LADs is increasingly prevalent in higher education (Corrin and De Barba, 2015). Feedback can be described as an interactive procedure where the result or impact of an action is returned to modify the subsequent action towards achieving a goal (Figure 2.2). In order to establish a connection between learners' previous and future work, facilitating a progressive developmental path, the importance of timeliness should be emphasized in any conversation about feedback (Sedrakyan et al., 2020).

According to the study conducted by Corrin and De Barba (2015), on how students perceive feedback delivered through LADs, valuable insights have been obtained regarding students' interpretation and action planning in response to such feedback. Contrary to concerns expressed in existing literature about students' ability to comprehend this type of feedback, the majority of participants in this study demonstrated a robust capacity for reflection and planning. The study found that the ability to access feedback had a positive influence on students' motivation, guiding them in their learning activities and assessments, leading to improved progress and performance.

2.4 Data collection

When talking about LA we are interested in three kinds of data that we call 3A's, according to Alyssa Wise [2] the three A's represent:
a. Activity: things that students do, like self-reports, log-files and physical traces.
b. Artifact: things that students create, such as problem answers and written explana-

[2] Alyssa Friend Wise the professor of Learning Sciences & Educational Technology at the Steinhardt School of Culture, Education, and Human Development, also serves as the network's director at New York University (NY-University, 2023).

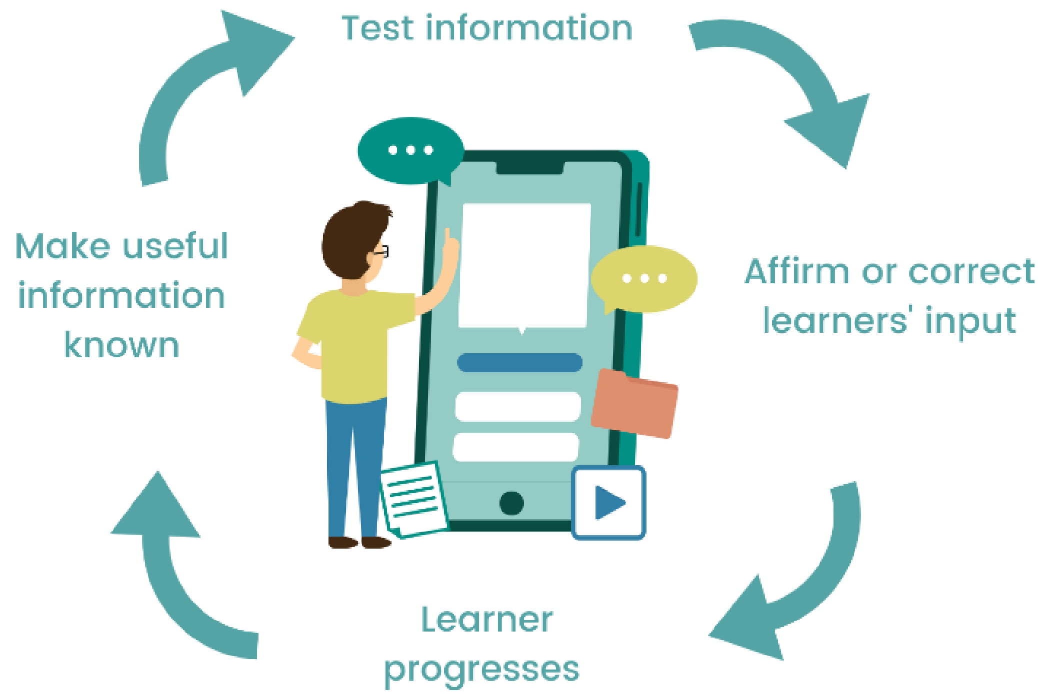

Figure 2.2: Feedback loop.
(Markovic, 2023)

tions.
c. Association: the connections that students make, like who and what they interact or communicate with.
Generally, the discipline of LA examines the educational data gathered from students' use of online resources. The majority of the data is gathered through LMSs that have been set up at valid educational institutions. Massive open online courses like Udemy, Coursera and Khan academy are also considered as rich sources of learners data (Wise, 2021).
There exists multiple tools and methods for the data collection phase, we will explore some of them in the next section.

2.4.1 Data collection methods and tools

First of all, we have to mention the content management instruction specification that was created by the Aviation Industry Computer-Based Training Committee[3] to establish guidelines for the seamless integration of web courses and LMSs. The content management instruction encompasses a data structure that captures student interactions with learning content and an application programming interface for managing this data. Using the content management instruction as a foundation, the data exchange model was developed by the IEEE[4] Learning Technology Standards. This model offers a wide range of fields to store various aspects of student interactions. Notably, it includes specific fields dedicated to recording general information about a student's level of progress in a particular activity (Del Blanco et al., 2013). However, a mechanism for tracking learner behavior called experience API may be used to collect the data, experience API makes it possible to trace a learner's behaviors during an activity as well as their learning experiences (Amrieh et al., 2015). Figure 2.3 represents an overview of the experience API mechanism.

Some researchers as Chen et al. (2014), used social media platforms to collect students data, they looked up for data in Twitter utilizing a Radian6[5] social media monitoring service with a paid educational account. They began by conducting a search using various boolean combinations of potential keywords, however the data set they obtained had roughly 35% noise. After that, they seeked students help by making a special hashtag, so the students use it when they post about education.
Another terminology called Linked Data is one of the interesting terminology used in the data collecting field. Linked Data employs Internet technology to connect data that may be stored in databases spread across several regions. Applications in the fields of

[3]The Aviation Industry CBT (Computer-Based Training) Committee (AICC) is a global organization that creates standards for the aviation sector's use of CBT and associated training technologies in their creation, delivery, and evaluation. The AICC's goals are to: • Help aviation operators create policies that encourage the efficient and cost-effective use of computer-based training (CBT); • Create policies that facilitate interoperability; and • Offer a public forum for discussion of CBT and other training technologies (Pagani, 2008).

[4]The IEEE is a renowned global organization committed to advancing technology for the betterment of humanity. With its influential publications, conferences, technology standards, and professional and educational initiatives, IEEE and its members inspire a worldwide community (**?**).

[5]Radian6 is a social media monitoring technology that allows marketers to track real-time consumer feedback on their products (Crunchbase, 2023).

Figure 2.3: Experience API overview.
(Rustici, 2023)

LA and EDM could be developed as a result of Linked Data technologies (Ang et al., 2020).

In their study Svihla et al. (2015), provoke students to make certain kind of steps and interactions with the learning environment components, so the data collected would be more specific to the case of study.

About massive open online courses the results of Deng and Benckendorff (2017) study, demonstrates that the most widely used methods for data collecting were surveys, interviews, and log files.

The data sensors such as cameras and microphones of different resources like face and voice are also used to capture data (Kouahla et al., 2022).

Finally, even with all these technological tools and methods, according to Ihantola et al. (2015); Matcha et al. (2019), the use of a questionnaire is still one of the most common methods of data gathering followed by log data and interviews in the third position.

2.4.2 The data needed to measure motivation

On real world, the teacher typically evaluates the student's facial expressions, voice, and body language to determine how the student is feeling. Looking at motivation as an emotion, Kouahla et al. (2022) stated that in order to identify emotions, we analyze the

learner's speech and facial expressions. That's what led them to gather specific kind of data using sensors and as a result they developed an approach called Emorec to detect and improve the students emotional state.
According to Salazar et al. (2021), the voice and face are the most common sources of emotional content in e-learning, and the best results come from face and spoken emotion recognition techniques. In contrast to other sensors, such as a skin sensor, the data sensors of these sources, such as the camera and microphone, are accessible to all students who learn using a PC or a mobile device (Kouahla et al., 2022).
In LMSs, there exists another way, tracking students behaviors. Talbi and Ouared (2022) used some metrics and indicators from the LMS just like tasks completion, assignments evaluations, current course grade, timing of starting activities...ect. Amraouy et al. (2020) also used the traces that students leave in an LMS to measure the motivation levels.

2.5 Learning analytics algorithms and models

The essential building blocks of the field of LA are its algorithms and models. By allowing the extraction of significant insights from enormous amounts of educational data, these powerful computational tools empower stakeholders and experts to take decisions based on data and improve the educational experience for students.

2.5.1 Learning analytics algorithms

A wide range of computational techniques are included in LA algorithms, which analyze educational data to find patterns, trends, and linkages. These algorithms are capable of processing a variety of data, including student demographics, engagement levels, test results, and learning activities. LA algorithms find significant patterns and produce useful recommendations to enhance teaching and learning methods by utilizing statistical, machine learning, and data mining techniques (Baker and Inventado, 2016; Paz and Cazella, 2019).

LA uses EDM to distill meaning (Baker and Inventado, 2016). There are numerous techniques used in education data mining, some of which include statistics, machine learning (neural networks, decision trees, deep learning), classification, regression, and clustering, social network analysis, text mining, web analytics and natural language processing, which makes LA uses Machine Learning algorithms indirectly (Hantoobi et al., 2021).

2.5.2 Learning analytics models

Frameworks and structures are provided by LA models for the interpretation and analysis of educational data. These models assist educators better understand students' actions, development, and learning outcomes by capturing the intricate relationships between many variables. LA models make it easier to spot trends and patterns that could otherwise go unnoticed.

Around 2011, the LA model progressed into its present form. Since then, LA models have been created in a variety of sectors in an ever-increasing quantity (Quadir et al., 2021). LA models, along with their objectives and constituent parts, are continuously updated in the field of education. The primary goals of LA models are to enhance learning and analyze the learning process using various instrumental investigations (Sengupta et al., 2020).

To begin with, it is important to acknowledge the foundational model developed by Chatti et al. (2012), they provided a reference model for LA that is based on four dimensions and list numerous issues and potential areas for research in regard to each dimension. The four dimensions of the suggested reference model for LA are shown in Figure 2.4, and are as follows:
What? What kind of data is collected, handled, and used for analysis by the system?
Who? Who is the analysis directed at?
Why? What justifies the system's analysis of the data gathered?
How? How does the system analyze the data that has been gathered?

Quadir et al. (2021) made a study about the categories of LA models from 2011 to 2019 (Figure 2.5). They end up with five categories, according to them these models are categorized based on the roles and the characteristics they have:

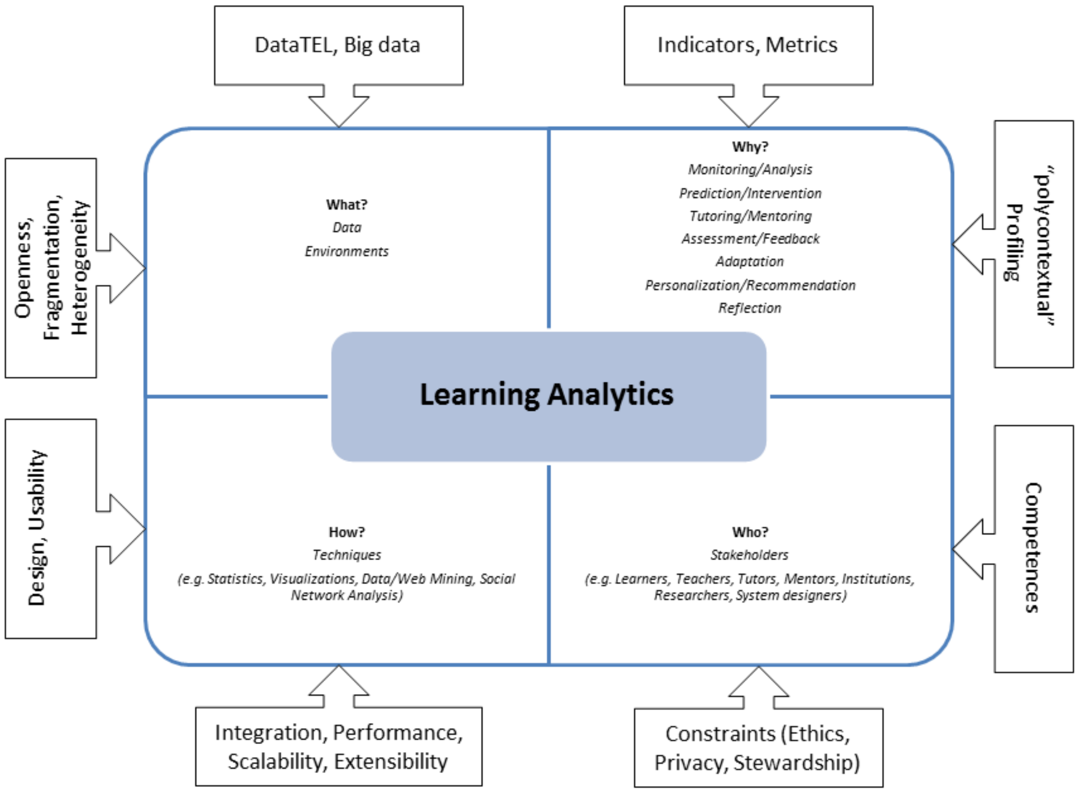

Figure 2.4: The learning analytics reference model proposed by Chatti et al. (2012).

Performance model

Models of performance include those that make claims about a learner's development, level of skills, or another claim about their competence with reference to their learning objectives.

Meta-cognitive model

Meta-cognitive model relates to the process of thinking about thinking or mental processes, refers to an implied mental state that is relevant to learning.

Interactivity model

Refers to a social activity that takes place inside an e-learning environment such as LMSs.

Communication model

Refers to a strong focus on the significance of the medium chosen, which may include face-to-face communication, Google forms, social learning platforms, rating, semantic richness, and network learning.

Data model

Refers to gathering all necessary data and remaining independent of every learning platform, includes a section to get comments from students on their educational experience, such as their level of success and completion, progress measurement, and score.

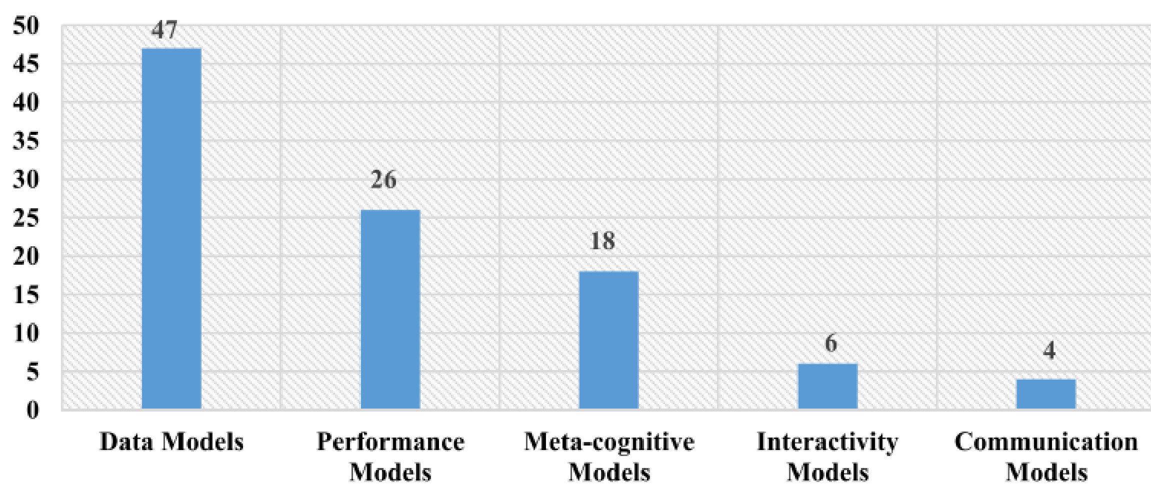

Figure 2.5: The distribution of categories among all the learning analytics models that were published between 2011 and 2019.
(Quadir et al., 2021)

In our case, the interactivity model is the most relevant one, because it focuses on the interactivity of students in a learning environment.

Finally, we have to mention the LA Predictive models, they are used to forecast academic, teacher, and learner performance with no parameters utilizing artificial methods including classification, regression, and prediction as well as time series analysis and decision trees (Ranjeeth et al., 2020). Many studies such as (Daud et al., 2017; Hantoobi et al., 2021; Nguyen et al., 2018), focused on utilizing LA to forecast learning results over time and notify students, using machine learning algorithms.

2.6 Visualization and design techniques

To enhance human cognition, visualization transforms the abstract and complex into the concrete and simple (Park and Jo, 2015). According to Duval (2011), many visualization are attractive, and some of them are quite lovely. But are they really delivering the right insights to taking decisions?
In order to support complicated cognitive processes like inference, judgment, and decision-making, visualizing data is a frequently used approach, the relevance of data visualization in both research and practice remains significant within the field of LA (Alhadad, 2018).

As stated by Yoo et al. (2015), three points from the literature are noteworthy with concerning visual perception. First, people can only keep three or four pieces of visual information at a time due to their limited working memory. Therefore, while creating a dashboard, it is preferable to use well-designed graphical patterns like graphs rather of individual numbers for effective perception and memory storage. Second, pre-attentive characteristics including color, form, spatial position, and motion should be effectively used for quick perception. Third, when building a dashboard, it is important to keep in mind Gestalt's principles[6] and take proximity, similarity, enclosure, and connection into account.

In LADs data representation is another topic that is debated. According to Matcha et al. (2019), bar charts as shown in Figure 2.6 were frequently utilized to display data. By using simple representations the LAD users find it easy to interpret the result. However, there aren't many empirical studies to guide the choice of visual representation for the dashboard's indicators, But using the Gestalt's principles will somehow facilitate this process.

[6]Gestalt's Principles are rules or laws of human vision that explain how people group pieces that are similar, notice patterns, and simplify complicated images as they view objects. These guidelines are used by designers to arrange content in a pleasing and understandable way on websites and other user interfaces (Foundation, 2022)

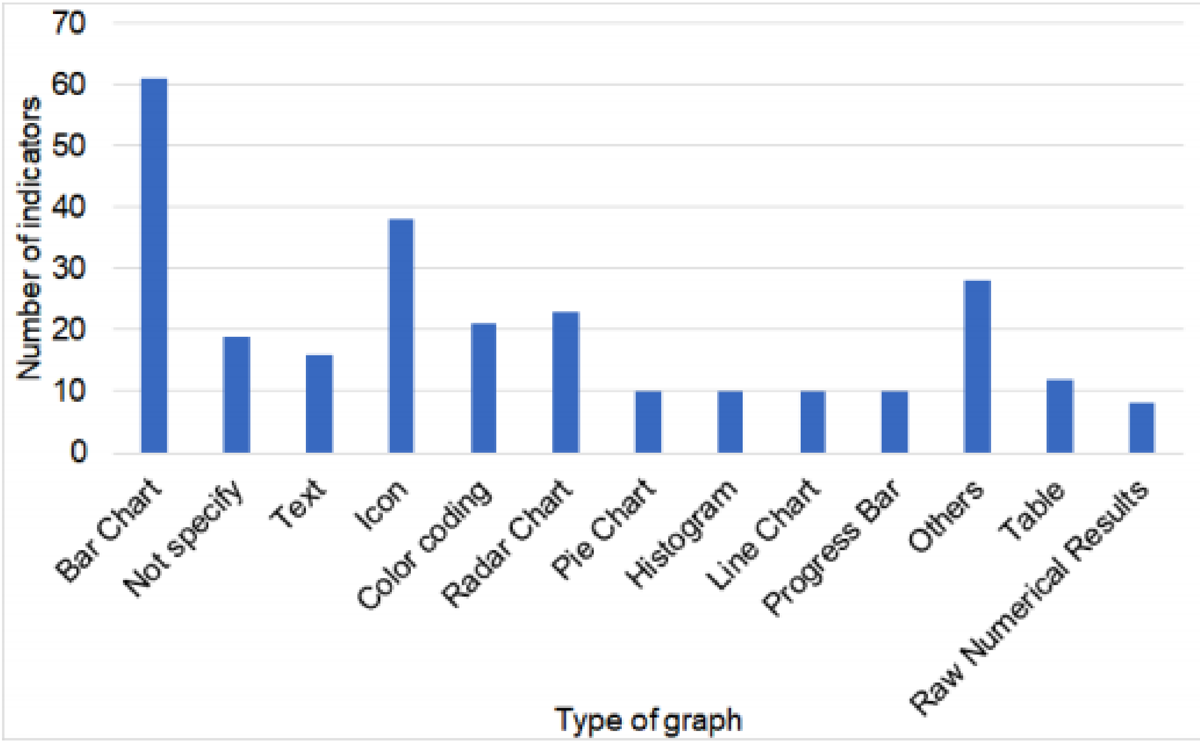

Figure 2.6: Visualisation types.
(Matcha et al., 2019)

2.7 Conclusion

In this chapter we explored the relation between LA and the student motivation detecting. We passed by the measurement of motivation and the descriptive level of LA that is so relevant to our vision. Then we mentioned the metrics and indicators, their power and value in the field of LA. We stated the most famous data collection tools and methods then the visualization techniques to visualize the data collected.
The subsequent chapter will encompass the process of designing the dashboard, utilizing the techniques discovered in the preceding chapter.

CHAPTER 3

Learning Analytics Dashboard for Motivation: Design

3.1 Introduction

In this chapter, we will systematically explore the design process of the dashboard, encompassing various stages. These include an overview of projects, the design of the database model, the establishment of student motivation indicators, the calculation of team motivation indicator, and lastly, the integration of motivation and feedback components.

3.2 Learning analytics and motivation detection process

Drawing upon the reference model of LA proposed by Chatti et al. (2012), and taking into consideration the most commonly employed components (refer to Figure 3.1), (Quadir et al., 2021), we constructed our motivation detection process. The components and their interrelationships are depicted in Figure 3.2.

At the core of the process lies the LMS, which serves as the starting point in the motivation detection life cycle. Next, we have the behavior component, which captures the students' interactivity within the LMS. Subsequently, we encounter the analytics component, functioning as the factory for generating motivation indicators. This is where Machine Learning or EDM models and algorithms may be utilized, such as classifying students into two categories: motivated and amotivated. The visualization component focuses on effectively representing the indicators, machine learning/EDM results, and placing them in the dashboard. This aids stakeholders in obtaining the most meaningful interpretations, facilitating decision-making and providing feedback.

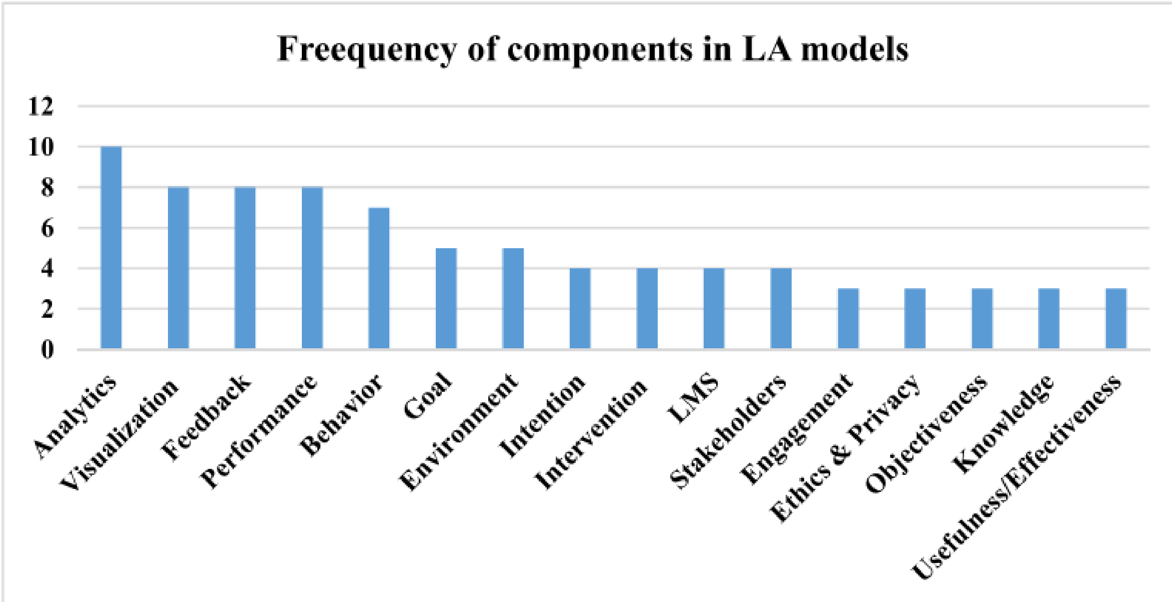

Figure 3.1: The most commonly used components according to Quadir et al. (2021).

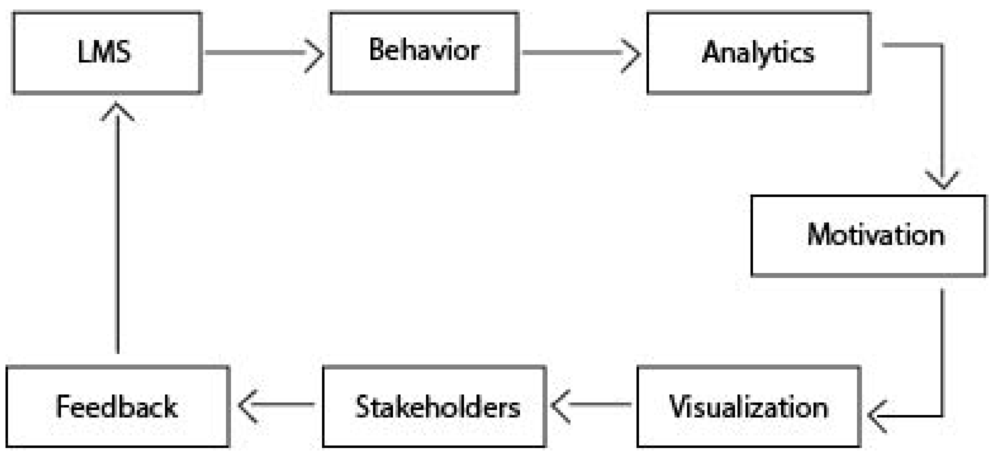

Figure 3.2: Learning analytics process for motivation detection.

To provide further clarity regarding our process, we present an overview in Figure 3.3, which elucidates the entire process of detecting students' motivation levels using LA and a dashboard for visualization.

3.3 The project's overview

Our approach embodies an interactive model, which hinges upon the collection of students' interactions and behavioral traces within a LMS. We posit that these behavioral

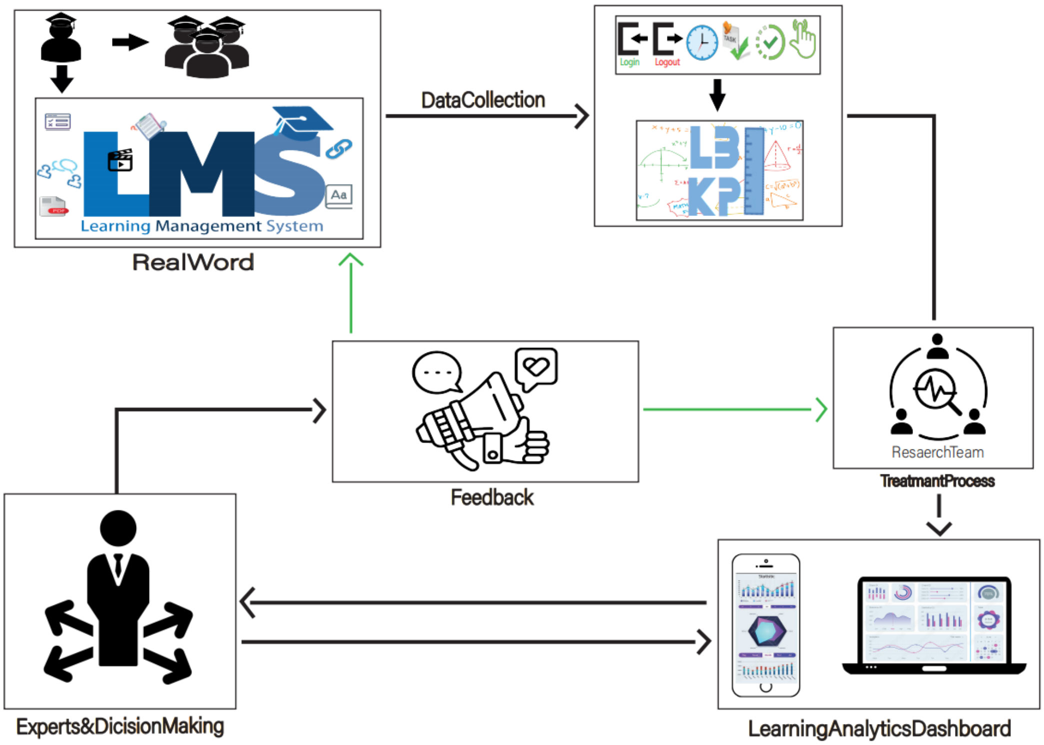

Figure 3.3: Overview of motivation detection using learning analytics.

patterns can be captured and quantified as metrics, facilitating their integration into our database for the purpose of computing motivation indicators.

Upon acquiring the necessary metrics, we utilized the motivation indicators proposed by Amraouy et al. (2020), as a foundation to construct our own set of motivation indicators. As a result, we derived four distinct indicators, specifically the collaboration indicator, effort indicator, interest indicator, and participation indicator. These indicators are calculated based on a compilation of ten metrics, with each indicator drawing upon two metrics, except for the interest indicator, which relies on four metrics.
As our approach does not employ any machine learning or EDM algorithms or models, we will directly visualize the motivation levels of students on the dashboard, leveraging the four aforementioned indicators (refer to Figure 3.4).

The ten metrics utilized in our framework encompass a range of factors, including Total Member Participation in WiKi, Total Team Members Participation in Wiki, Time Mobilized in Activities, Expected Time to Complete Activities, Total Accomplished Activities, Total Suggested Activities, Total Learner Relevant Participation in Forum [1],

[1] Typically obtained through the utilization of Natural Language Processing for retrieving relevant texts (Litman, 2016).

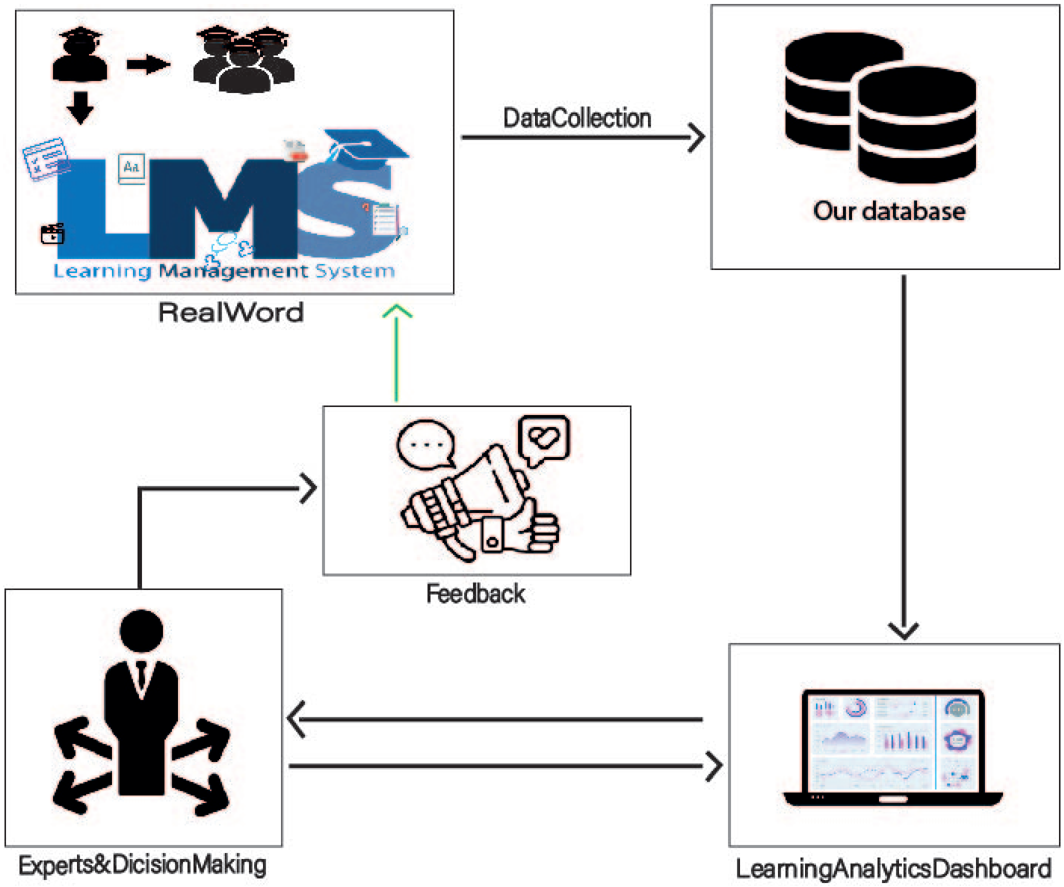

Figure 3.4: Overview of motivation detection using motivation indicators.

Total Learner Participation in Forum, Total Learner Clicks, and Expected Amount of Clicks.

3.4 The database model

Considering the fact that data acquired from an LMS is gathered, received, and stored in a database, and keeping in view the concept put forth by Djouad and Mille (2018), that a table can be used to define an indicator in a database schema, our suggestion is to introduce a schema that fulfills these needs (Figure 3.5).

The schema begins with multiple teams, each consisting of several members, where each student is a member of a team. Both students and teams have their own feedback archives. Each student has one or more metrics associated with them, and each metric is connected to one or more students. Additionally, indicators are calculated based on one or more metrics, and each metric is used to calculate one or more indicators.

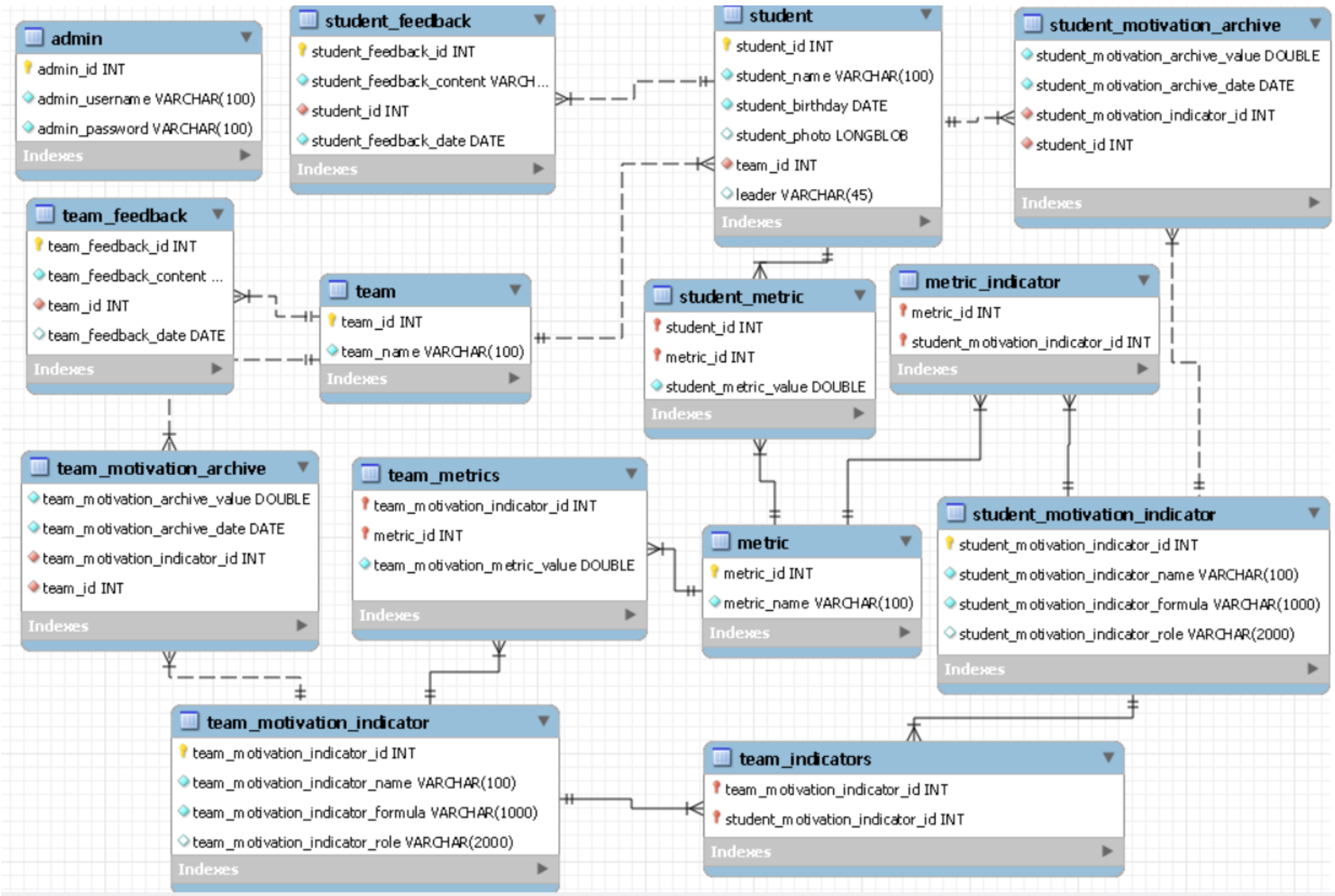

Figure 3.5: Entity-relationship diagram of Our database.

To measure team motivation, team motivation indicators are computed using one or more metrics/indicators, and each metric/indicator is utilized to calculate one or more team motivation indicators. Each student and team maintains a history of their motivation indicators and feedback.
Finally, an admin table exists to facilitate authentication for stakeholders.

3.5 Student motivation indicators

In this section, we will delve into the four indicators of student motivation. We will begin by providing a brief explanation, followed by the mathematical formula associated with each indicator.

3.5.1 Collaboration indicator: Collaboration plays a crucial role in creating effective learning environments, and understanding the extent to which students engage in collaborative activities provides valuable insights into their involvement and participation (So and Brush, 2008). This indicator (Figure 3.6) shows the position of the student in his team by comparing his participation and the total team members participation in wiki, a wiki is a type of technology associated with Web 2.0 that places great importance on collaborative writing, allowing individuals to contribute by adding, modifying, or removing content. The inclusive and accessible nature of wikis presents valuable prospects for acquiring knowledge, making them effective tools for facilitating group learning. Utilizing wiki as a collaborative tool enhances writing abilities and fosters the acquisition of knowledge. Additionally, wiki projects have the potential to encourage the collaborative creation of knowledge (Altanopoulou and Tselios, 2017).

$$Collaboration = \frac{Total\ Member\ Participations\ in\ WIKI}{Total\ Team\ Members\ Participations\ in\ WIKI} * 100$$

Figure 3.6: Collaboration indicator formula.

3.5.2 Effort indicator: The level of effort exerted by students is crucial in determining their engagement and commitment towards their learning journey (Cambria and Guthrie, 2010). In any learning environment, students are given tasks with specific time expectations for completion. By comparing the actual time students spend on a task to the expected time, we can gauge their effort level (Trautwein, 2007; Xu, 2013). This indicator (Figure 3.7) shows how much time a student spend solving or doing his activities. According to Nagy (2016), in the field of education, emphasizing student effort instead of solely focusing on their achievements is similar to directing attention towards the process rather than the end result. This approach ensures that the educational system values the fundamental qualities of a successful student rather than merely the outcomes they attain.

3.5.3 Interest indicator: In a learning environment, giving students the freedom to make choices and take ownership of their learning is crucial for fostering motivation and engagement (Deci and Ryan, 2000). The interest indicator (Figure 3.8) provides

$$Effort = \frac{Time\ Mobilized\ in\ Activities}{Expected\ Time\ to\ Complete\ Activities} * 100$$

Figure 3.7: Effort indicator formula.

insights into the level of a student's engagement in their learning journey. The more the student actively completes tasks, seeks out new activities, or interacts with the content by clicking on it, the stronger the indication of their motivation. Some studies as Svihla et al. (2015), putted a roadmap in the LMS for students so they can collect special data including their clicks and accessed contents.

$$Interest = \left(\left(\frac{Total\ Accomplished\ Activities}{Total\ Suggested\ Activities} * 100\right) + \left(\frac{Total\ Learner\ Relevant\ Clicks}{Total\ Learner\ Clicks} * 100\right)\right)/2$$

Figure 3.8: Interest indicator formula.

3.5.4 Participation indicator: Active participation is a key aspect of effective learning environments, and the indicator of participation allows us to gain insights into the level of engagement and involvement of students (Freeman et al., 2014). This indicator (Figure 3.9) is about how much the student is good in his responses and participation in forum, forums are considered as a powerful type of activities which help and support the team members communication (Andresen, 2009).

$$Participation = \frac{Total\ Learner\ Relevant\ Participations\ in\ Forum}{Total\ Learner\ Participations\ in\ Forum} * 100$$

Figure 3.9: Participation indicator formula.

3.6 Team motivation indicator

We present a holistic indicator for the team motivation, encompassing the integration of the four Student Motivation Indicators. Through the utilization of a weighted average

formula. We utilize a weighted average formula to incorporate the differing levels of significance of numbers within a dataset. By employing this computation method, each number is multiplied by a predetermined weight prior to the final calculation. The use of a weighted average enhances accuracy in contrast to a simple average, which treats all numbers equally without considering their varying importance (GANTI, 2023).
Each indicator's value contributes to the calculation, reflecting its significance within the team. Moreover, recognizing the pivotal role of the team leader in motivating the team (Chen et al., 2011; DÜŞÜN and DEMİR, 2012). We assign a distinct weight to the leader's motivation level, differentiating it from that of other team members.

3.7 Visualization

Well-designed dashboards contribute to both effective communication and accurate decision-making (Alhadad, 2018).
The following design principles are outlined: Firstly, the crucial information within the dashboard should be distinguishable from the rest, considering the limited space typically available. Secondly, the information displayed should enhance situational awareness and facilitate quick comprehension by utilizing various visualization technologies. Thirdly, the deployment of information should be logical, with its elements supporting the stakeholders immediate and ultimate goals in the decision-making process (Park and Jo, 2015).
By applying these principles and considering the principles of Gestalt (Yoo et al., 2015), and ultimately utilizing the simplest and commonly used charts (Matcha et al., 2019), we will create visual representations of the four student motivation indicators and the team motivation indicator by employing the following charts (Figure 3.10):

3.7.1 Bar chart

A bar chart is a visual representation that uses bars of varying heights to illustrate information and values. Its purpose is to efficiently convey relational information in a visual format. The bars represent the values corresponding to specific categories of data. Bar graphs are frequently utilized in business and financial analysis to present complex data in a clear and concise manner, allowing for swift and effective information communi-

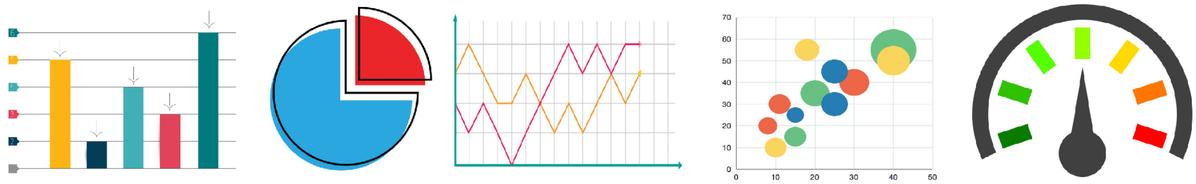

Figure 3.10: Visualization charts.

cation (Mitchell, 2022). Within our LAD, this chart will depict the percentage of effort contributed by each student in comparison to their team members.

3.7.2 Pie chart

The collaboration indicator which represents the percentage of the students' participation in Wiki compared with the total team members participation in Wiki will be associated to a pie chart, since the total value of the pie is always 100% (BYJU, 2023). A pie chart is a visual representation method that presents data in a circular graph format. It is a static chart suitable for displaying a small number of variables. Pie charts are commonly employed to illustrate sample data, where data points fall into various categories. Each category is depicted as a "slice of the pie," with the size of each slice directly proportional to the number of data points associated with that specific category (TIBCO, 2023).

3.7.3 Line chart

The line charts employ markers representing data points that are connected by straight lines, facilitating visual representation. These line graphs find utility across diverse domains and serve various objectives (Peters, 2022). The purpose of this chart is to display the varying values of the participation indicator for each individual student.

3.7.4 Bubble chart

A bubble chart is a type of data visualization that showcases multiple circles, also known as bubbles, within a two-dimensional plot. It serves as an extension of the scatter plot, replacing individual dots with bubbles. Typically, a bubble chart represents the values of three numeric variables, with each observation's data represented by a circle or bubble. The position of the bubble on the horizontal and vertical axes corresponds to the values of two other variables, providing a comprehensive view of the data (Bock, 2018). The bubble chart will be employed to depict the interest indicator percentages for every student.

3.7.5 Gauge chart

A gauge chart, also referred to as a speedometer chart or dial chart, is a widely employed visual tool for representing progressive values. It resembles a speedometer or a dial, with a needle indicating a specific value over a central pivot point. The dial typically incorporates various colors to divide the scale into distinct segments, enabling a clear comprehension of the information.

When the range is limited, it is common to use a half or quarter pie to illustrate the scale. However, when comparing an extensive range, a speedometer is often employed instead of a dial. In such cases, the visual representation is known as a speedometer chart, which is a variant of the gauge chart. Due to their simplicity and widespread usage, gauge charts find application in various scenarios (Edrawmax, 2023). In our LAD, we will employ a gauge chart to visually represent the total motivation levels of the entire team.

3.8 Feedback

Offering feedback and suggestions for growth. Feedback enhances student motivation by helping them gauge their progress, identifying areas needing attention, and guiding them toward improvement (Wang et al., 2023).

Because of their significant role in enhancing the learning experience (Corrin and De Barba, 2015; Sedrakyan et al., 2020), we propose allowing stakeholders to provide diverse forms of textual feedback to both students and teams. The feedback received from stakeholders will be saved in our database and presented in a table format, facilitating stakeholders' ability to recall which students or teams have received feedback along with their corresponding dates.

3.9 Use case diagram

In order to illustrate the interactions between a stakeholder and the LAD, we developed a use case diagram (Figure 3.11).

Once the stakeholder logs in, they have the option to select a team. Only after selecting a team the stakeholder can access the student motivation indicators and the team motivation indicator, which will be displayed in the dashboard. It is important to note that a stakeholder cannot create an indicator, provide feedback, or view team or student information unless they have chosen a team. To create an indicator, the stakeholder must first select the necessary metrics for its calculation. Similarly, when providing feedback, the stakeholder is required to specify the recipient. Without selecting the metrics or specifying the recipient, the stakeholder is unable to create an indicator or send feedback, respectively.

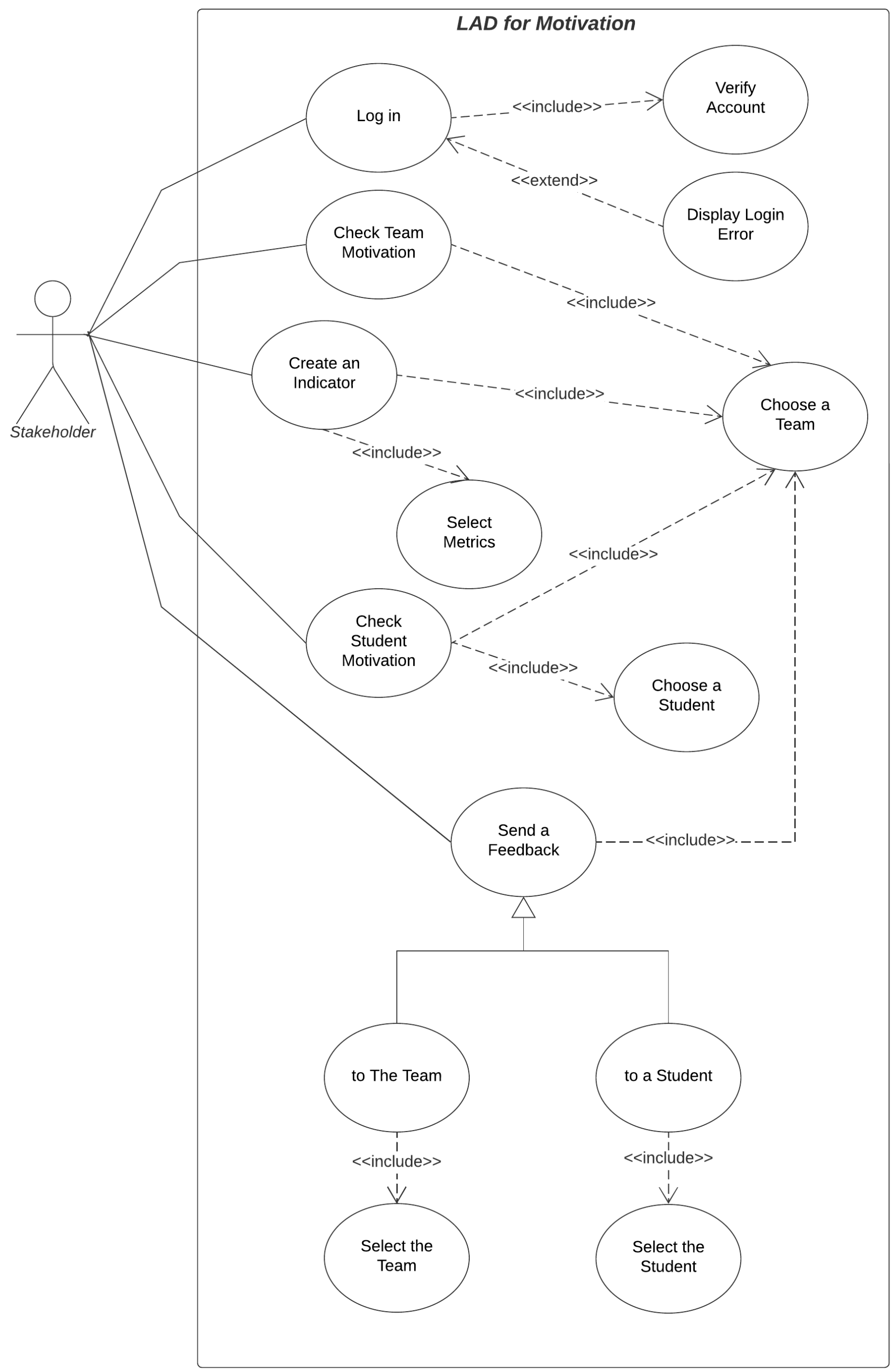

Figure 3.11: Use case diagram of the learning analytics dashboard for motivation.

3.10 Conclusion

In conclusion, this chapter provides a comprehensive overview of the step-by-step design process involved in creating the dashboard. The upcoming chapter will demonstrate the process of incorporating our dashboard.

CHAPTER 4

Realization of the prototype

4.1 Introduction

To bring our prototype to life, we employed a wide array of tools, in the first section of this chapter we will give an overview and a definition of each tool utilized. Next, we proceed to examine the outcomes obtained following the implementation of our dashboard.

4.2 Tools

4.2.1 Integrated development environment

Intellij IDE overview

Intellij is a comprehensive Integrated Development Environment tailored for Java vertuel machine languages, aims to optimize the efficiency of developers. By offering intelligent code completion, thorough code analysis, and automated refactoring, it relieves programmers of mundane and repetitive tasks. Consequently, it allows individuals to concentrate on the positive aspects of software development, transforming it into a productive and pleasurable endeavor (Jenkov, 2018).

4.2.2 Languages

Java

The Java technology encompasses both an object-oriented programming language and a computer platform. Created by Sun Microsystems (often referred to as "Sun") in 1995 and subsequently acquired by Oracle in 2009, Java technology is inseparable from the field of computing and the web. It is found not only on computers but also on mobile phones, gaming consoles, and more. The advent of smartphones and the increasing power of computers have led to a renewed interest in this programming language (CCM, 2019).

Unified modeling language

Unified modeling language, known as UML, is a graphical representation tool used by software developers to visualize and create novel systems. Unlike a programming language, it consists of a set of guidelines solely dedicated to creating diagrams. While various software engineering diagrams exist, UML can be likened to a blueprint that software engineers utilize to outline their designs (Gliffy, 2022).

4.2.3 Database

MySQL database management system

In order to store the data we need to develop our LAD for Motivation, we used a database management system. For this role we chose MySQL.
MySQL, a widely used SQL database management system that is available as open-

source software, is developed, distributed, and supported by Oracle Corporation. MySQL serves as a system for managing databases (MySQL, 2023).

MySQL Workbench

With MySQL we used MySQL Workbench which is a comprehensive graphical application designed to cater to the needs of database architects, developers, and DBAs. It serves as a unified tool that offers functionalities such as data modeling, SQL development, and an extensive array of administration tools for tasks like server configuration, user management, backup operations, and many additional features (Workbench, 2023).

4.2.4 Technologies

JavaFX

Considering our LAD for motivation as an application, we chose JavaFX to develop it, JavaFX application code, implemented as a Java API, enables the utilization of APIs from various Java libraries. These libraries offer access to native system capabilities and the ability to connect with server-based middleware applications.

JavaFX encompasses a collection of graphics and media components that empower developers to conceive, build, verify, troubleshoot, and distribute feature-rich client applications that maintain consistent functionality across various platforms. JavaFX applications possess customizable aesthetics and visual elements. By utilizing Cascading Style Sheets, developers can separate the appearance and style from the implementation, enabling them to focus on coding. Graphic designers have the flexibility to easily modify the application's appearance and style using CSS. Those with a background in web design, or those seeking to separate the user interface from the back-end logic, have the option to develop the user interface's presentation aspects using the FXML scripting language, while employing Java code for the application logic. Alternatively, JavaFX Scene Builder can be utilized for user interface design without the need for coding. As the user interface is designed, Scene Builder generates FXML markup that can be transferred to an Integrated Development Environment, allowing developers to incorporate the business logic (Pawlan, 2013).

FXML file: JavaFX FXML is an XML-based format that allows you to construct JavaFX graphical user interfaces (GUIs) in a manner reminiscent of creating web GUIs with HTML. By utilizing FXML, you can effectively segregate your JavaFX layout code from the remainder of your application code. This separation improves the organization and cleanliness of both the layout code and the rest of the application code.

FXML is versatile and can be employed to design the layout for an entire application GUI or just a specific portion, such as the layout for a particular section of a form, tab, dialog, and so on (JetBrains, 2023).

Scene builder: JavaFX Scene Builder is a graphical interface design tool that enables users to swiftly create visually appealing user interfaces for JavaFX applications, all without the need for coding. Through an intuitive drag-and-drop approach, users can effortlessly place UI components onto a workspace, adjust their attributes, apply style sheets, and observe as the corresponding FXML code is automatically generated in the background. This process yields an FXML file that can be seamlessly integrated into a Java project by establishing connections between the UI elements and the application's underlying logic (Oracle, 2023).

Medusa: This project employed a gauges JavaFX library called Medusa, with the primary emphasis on offering versatile configurations for gauges (HanSolo, 2021).

4.3 Learning analytics dashboard for motivation: prototype

In this section, we will showcase the implemented prototype of our LAD for motivation.

4.3.1 The dashboards' user interface

In this section, we will display the user interface of the LAD. Each screenshot presented represents a particular state or view of the dashboard.
Upon initial execution of the dashboard, it appears empty, and all action buttons, except for the search option, are disabled (Figure 4.1).

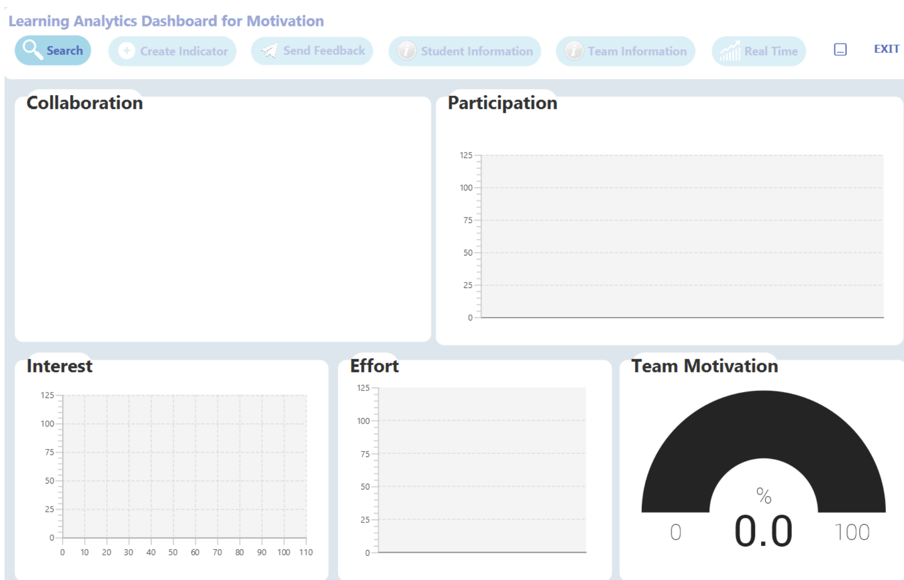

Figure 4.1: Learning analytics dashboard for motivation (empty).

Once the stakeholder chooses a team (they can do so by conducting a search for either the team itself or one of its members 4.2), they will have access to the visualization of the motivation indicators for each student, as well as the overall motivation indicator for the team (Figure 4.3).

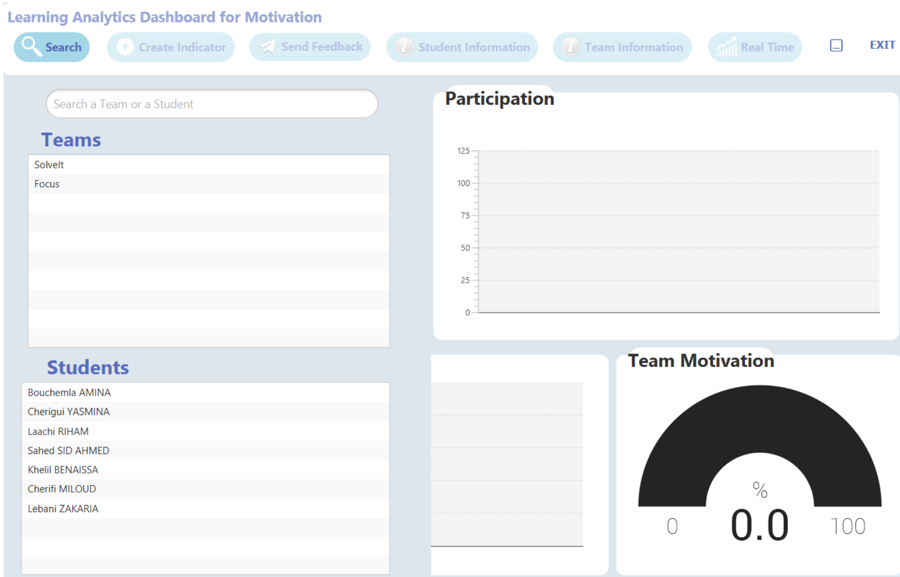

Figure 4.2: Search slider.

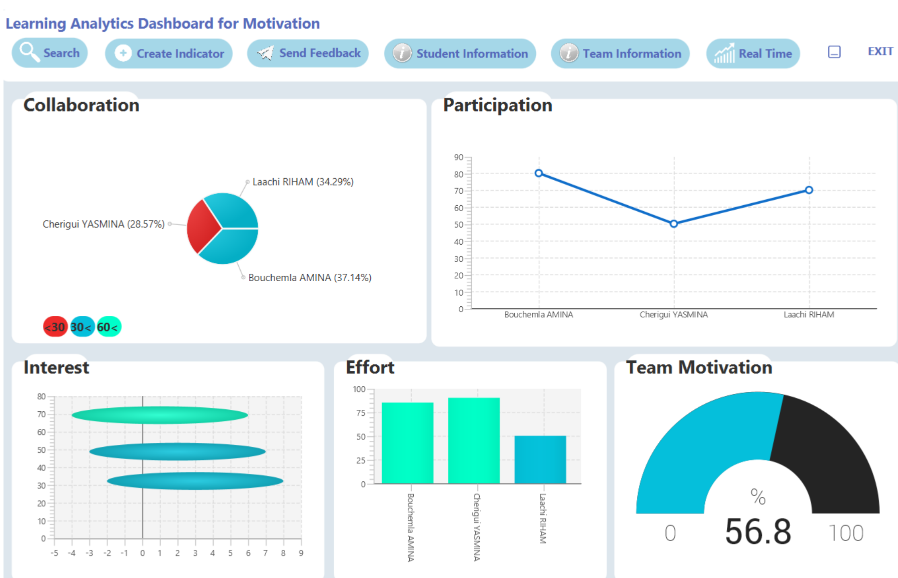

Figure 4.3: Learning analytics dashboard for motivation view.

The stakeholder lacks the ability to create an indicator until they have chosen the necessary metrics for its calculation and assigned it a name (Figure 4.4).

Once the stakeholder has fulfilled the requirements, they will be able to observe the visualization of the indicator they have generated (Figure 4.5).

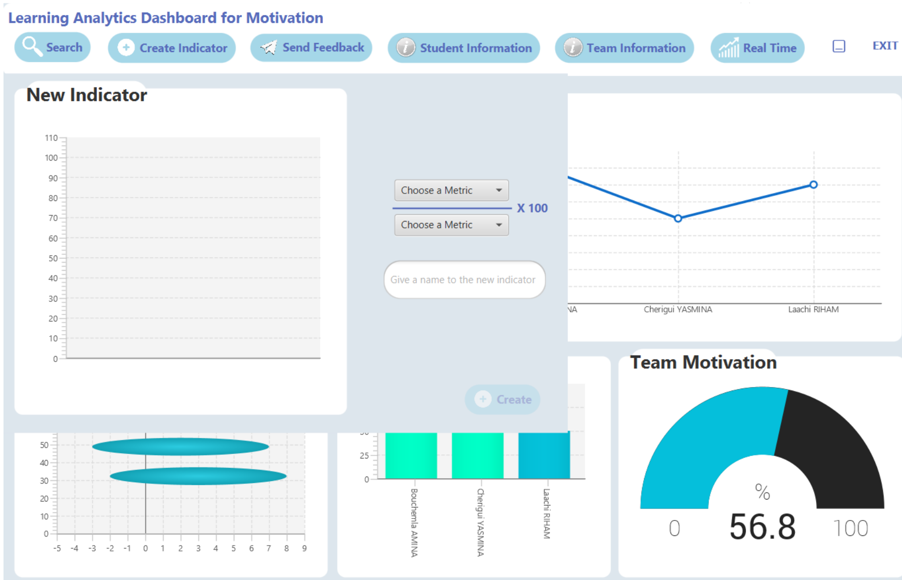

Figure 4.4: Create an indicator slider (before).

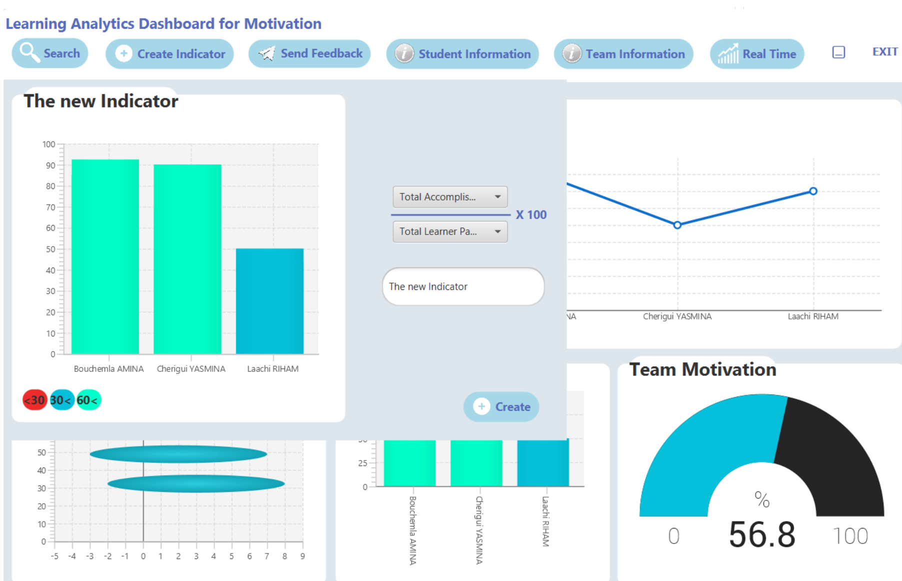

Figure 4.5: Create an indicator slider (after).

The same principle applies to providing feedback. Without selecting the necessary requirements (Figure 4.6), a stakeholder is unable to submit feedback. Only after fulfilling the requirements can they proceed with providing feedback (Figure 4.7).

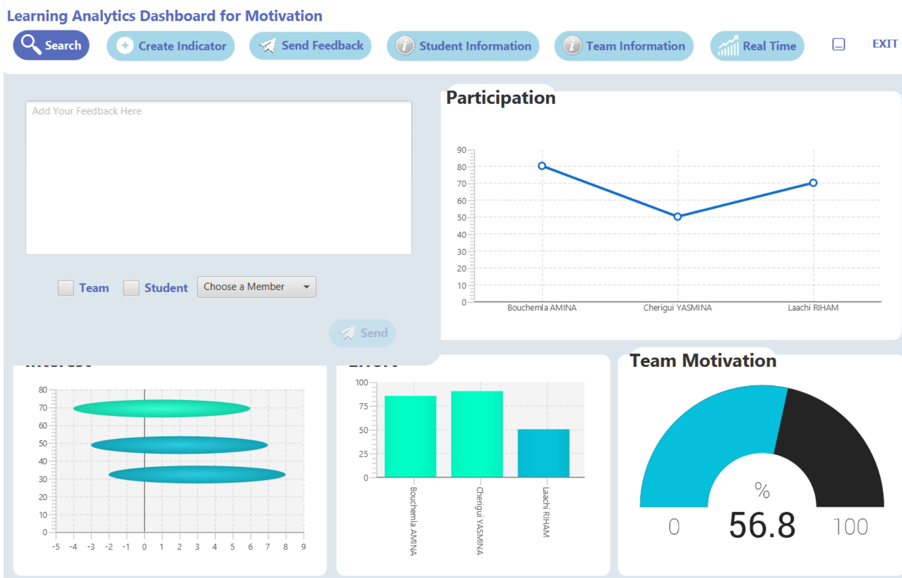

Figure 4.6: Send a feedback slider (before).

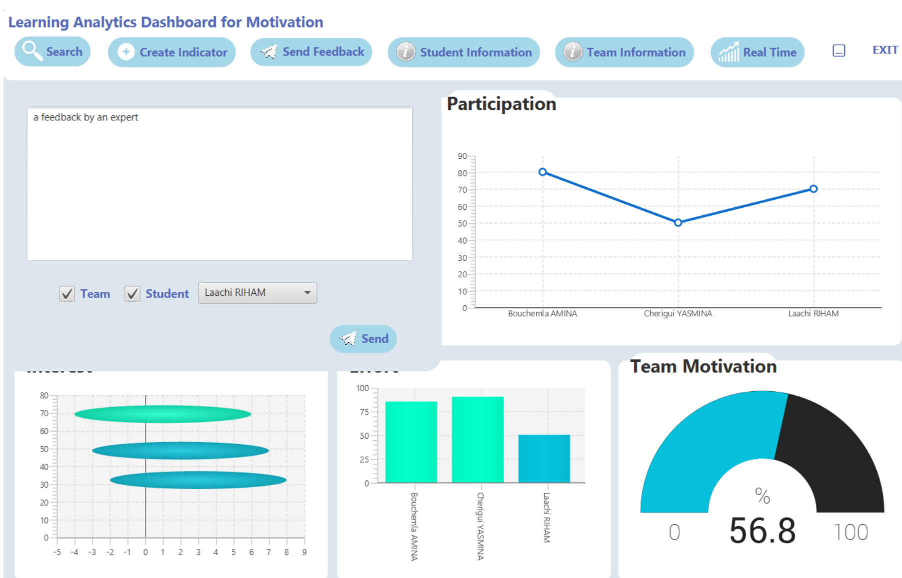

Figure 4.7: Send a feedback slider (after).

After selecting the name of a team member, a stakeholder can access their individual information (Figure 4.8, Figure 4.9). Similarly, the stakeholder can also review the collective information of the entire team (Figure 4.10).

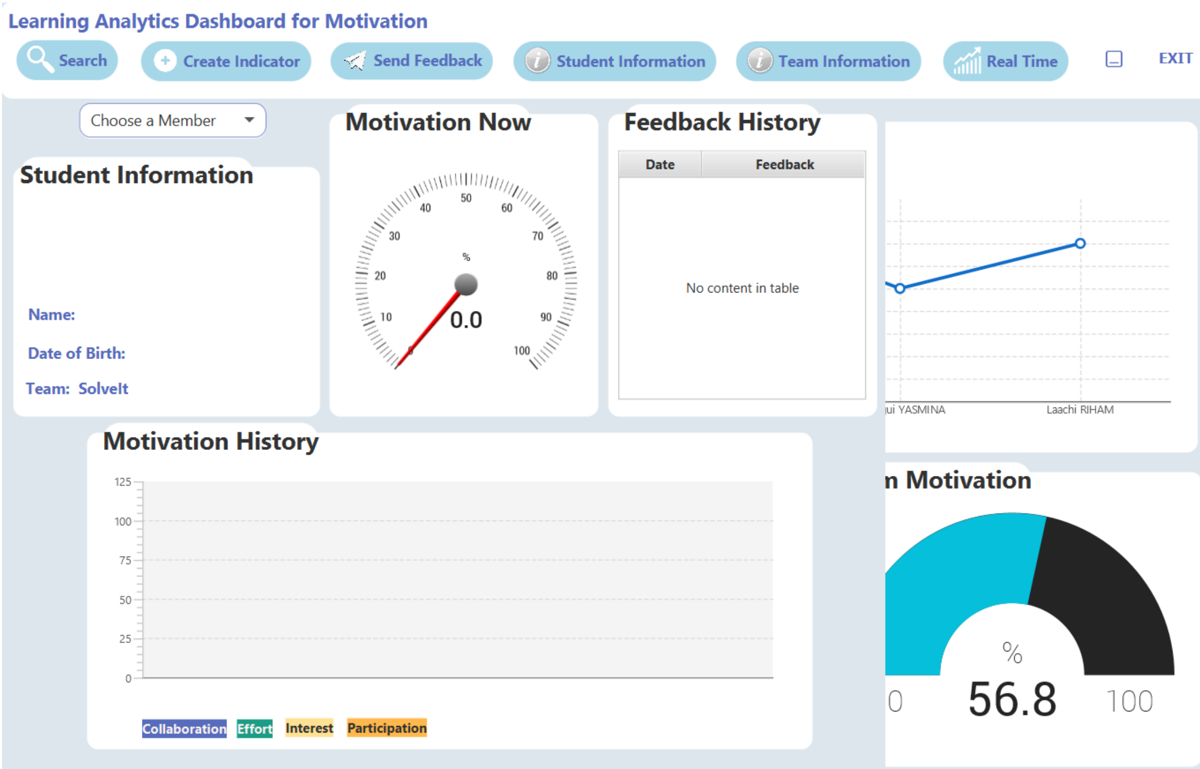

Figure 4.8: Student information slider (before).

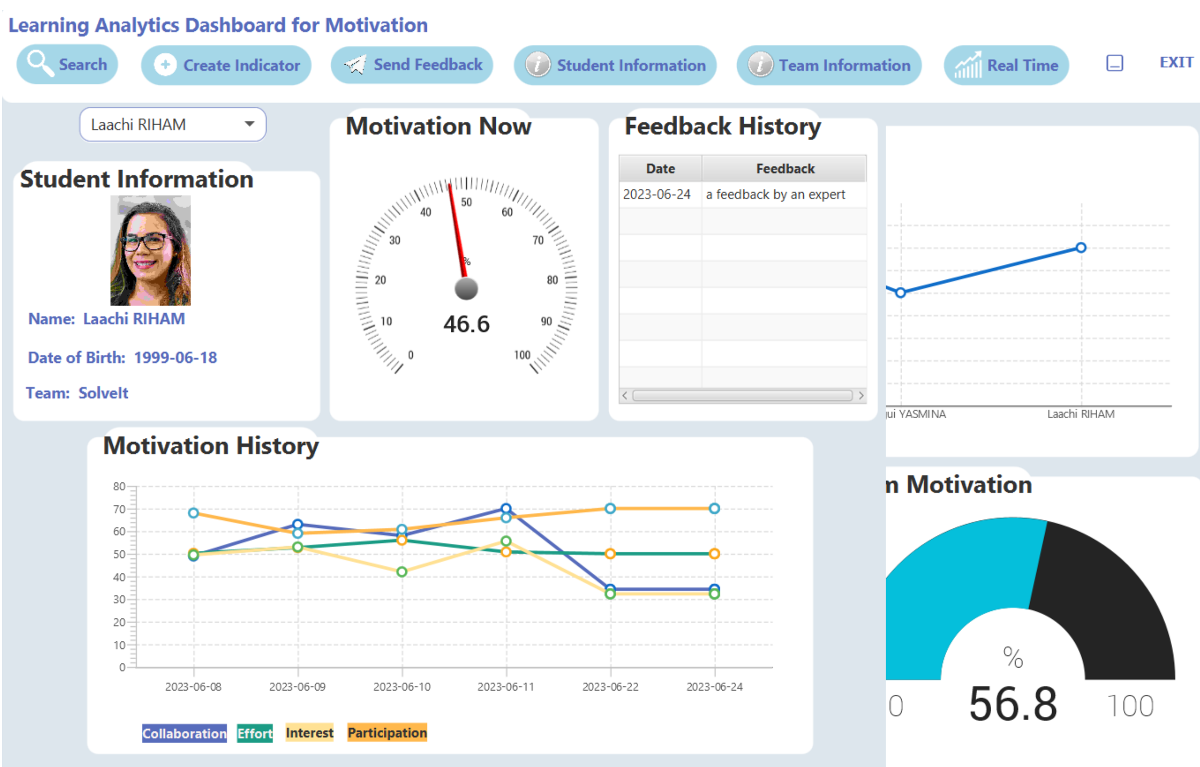

Figure 4.9: Student information slider (after).

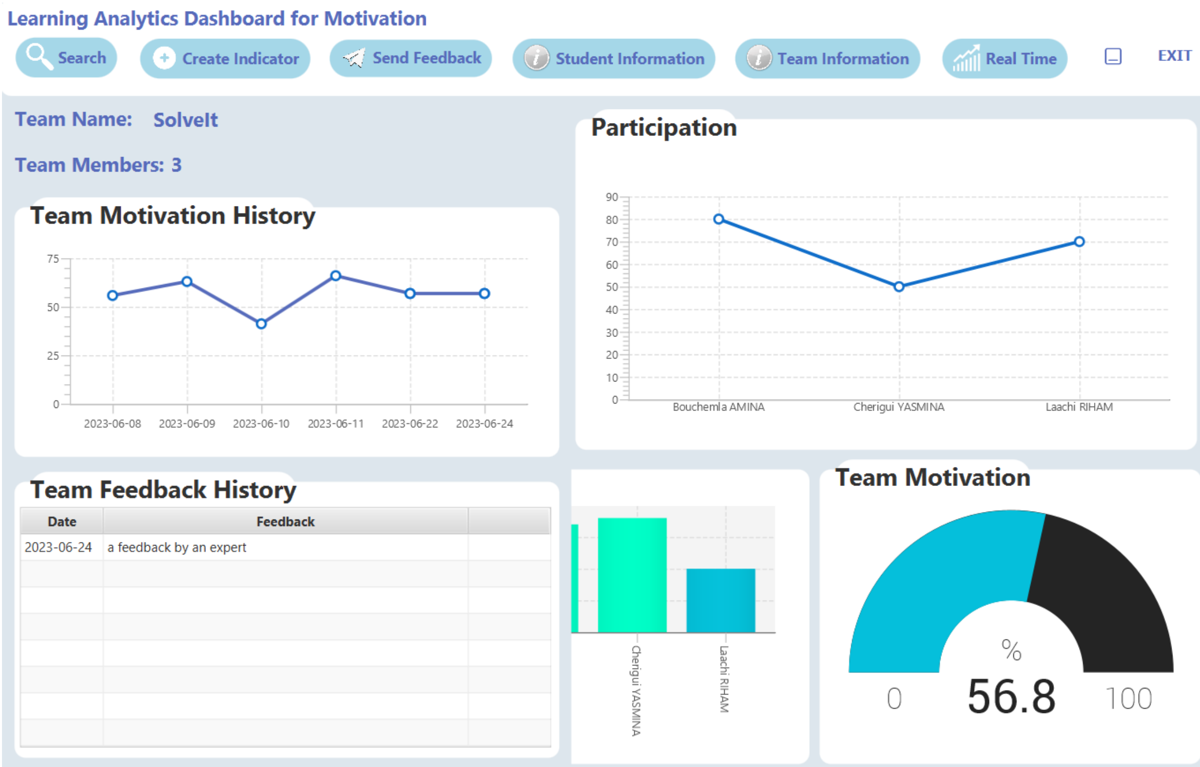

Figure 4.10: Team information slider.

4.4 Conclusion

In conclusion, this chapter highlights the significance of the dashboard in providing stakeholders with comprehensive insights into team dynamics and individual member motivation. The dashboard offers visual representations of indicators, and enables stakeholders to provide feedback effectively. By granting access to specific information about team members, the dashboard supports informed decision-making and fosters collaboration within the learning environment. The implementation of this dashboard proves instrumental in facilitating efficient monitoring and assessment of team motivation, ultimately contributing to the overall success of the educational process.

General conclusion

This thesis is organized into four main chapters. The first and second chapters are dedicated to theoretical aspects.

The initial chapter provides an overview of the current state of the field, which includes background information on the integration of ICT in education, LMS, LA, LAD, PjBL, as well as a problem setting and a related works sections.

The second chapter specifically focuses on the relationship between motivation and LA, highlighting how LA can provide valuable insights into students' motivational states. It also explores the importance of well-designed LAD with effective visualizations and their impact on stakeholders' interpretations and decision-making.

The focus of the third chapter revolves around designing the LAD. It starts with the creation of a LA model and concludes by selecting appropriate components for effective visualization.

Lastly, the fourth and final chapter delves into the tools employed during the implementation process, including Integrated Development Environments, programming languages, technologies, and so on. Additionally, this chapter presents the ultimate outcome of the research.

Perspectives

The project presented here can be viewed as an entry point to explore new possibilities. It suggests that future studies could focus on various indicators of motivation on a large scale, potentially leading to the development of a classification machine or deep learning model. This model would be capable of categorizing students and teams into two groups: motivated and unmotivated. Additionally, researchers could work on designing a LAD that visually represents predicted motivation levels. This would empower stakeholders, including students, to make more informed decisions and increase their chances of achieving success. The dashboard developed in this project has the potential to be converted into a mobile application, making it easier for students to utilize. This mobile application would enable students to monitor their motivation levels as well as their team's motivation. Lastly, there is a strong desire for real-time synchronization of data from LMS and massive open online courses to accurately reflect motivation levels as they occur.

Conclusion

This thesis represents a small contribution within the rapidly evolving field of LA. It acknowledges that there is much room for improvement in terms of refining our work to achieve optimal performance and availability. However, due to time constraints and limited resources, further future enhancements are necessary to reach the desired level of excellence.

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